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Three Essays on the Selection Effect of Trade and Labor Market Rigidity

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THREE ESSAYS ON THE SELECTION EFFECT OF TRADE AND LABOR MARKET RIGIDITY

by

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ABSTRACT

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Three Essays on the Selection Effect of Trade and Labor Market Rigidity

Dissertation directed by Professor Robert McNown

This dissertation investigates the impact of labor market conditions on the selection effect that trade causes. Since the selection effect can affect the labor market outcomes positively, this includes issues pertaining to improve the worker's welfare in the long term. As a result, the main goal of the dissertation is to investigate which labor market conditions can boost the aggregate total factor productivity as the economy is more open to trade.

In the first chapter, I examine when trade could cause the selection effect. If the increased average real wage induced by trade triggers the selection effect (Melitz, 2003), the main issue is to determine the labor market conditions under which trade raises the average real wage. According to the results of regressions of the average and 10th percentile of residual wages, this paper shows that with high union density, low job destruction, and low job creation, the effect of trade on the average residual wage is likely to be negative because the impact of imports exceeds that of exports. Moreover, the impact of trade on the average wage must work through the residual wage because this study does not find any significant impact of trade on average predicted wage. As a result, the more rigid the labor market is, the

less likely trade is to raise the average industrial wage and the less likely the selection effect in Melitz (2003) is to occur.

In the second chapter, based on the results from the first chapter, I examines whether job flows can improve the aggregate total factor productivity by using U.S. industry data set.

In the third chapter, it investigates how rigidity in labor market institutions influences the selection effect as the economy is more open to trade. Findings from dynamic ordinary least square (DOLS) suggest that higher labor market rigidity in an open economy reduces the TFP through the negative selection effect. In particular, in extremely high rigidity but low foreign R&D stock, the openness to trade could cause the country to experience decreasing TFP because the negative selection effect can offset the international R&D spillover effect.

To My Wife, My Daughter and My Son

CONTENTS

TABLES

Table

FIGURES

Figure

CHAPTER I

TRADE AND WAGE DISTRIBUTION DYNAMICS: WHEN DOES TRADE CAUSE THE SELECTION EFFECT?

I.1 Introduction

The aggregate productivity gains from trade liberalization can be boosted mainly through the reallocation process of domestic resources toward more productive firms, i.e. the selection effect of trade.[1] Felbermayr, Prat, and Schmerer (2008) have attempted to connect the aggregate productivity gains with the long run impact of trade on labor market outcomes; that is, as long as the selection effect of trade exists, trade liberalization lowers unemployment and raises the real wage in the long run. Implications for aggregate productivity dynamics could shed new light on the early debates focusing on the short run and static impact of trade on labor market outcomes. However, trade does not always induce the selection effect in long run equilibrium. Certain conditions in a period of transition need to be satisfied. Otherwise, the selection effect may not occur, or a negative selection effect might even occur, as suggested in Archarya and Keller (2008) and Melitz and Ottaviano (2008). In particular, this paper demonstrates that the labor market can be involved in determining the extent to which trade causes the selection effect in the long run. As a result, to investigate the long run impact of trade on labor market outcomes,

[1] In this paper, the selection effect implies a positive selection effect.

we should focus on the labor market conditions in the transition path of the selection effect.

This paper attempts to identify the labor market conditions that induce the selection effect of trade. Accordingly, my work builds on Melitz (2003) that suggests the labor market competition as a mechanism through which the selection effect of trade occurs.[2] Melitz's (2003) argument reading the selection effect is that the increase in average real industrial wage induced by exports pushes up aggregate productivity by removing the least productive firms from the market. That is, the increased average real wage triggers the selection effect. Despite the critical role of the increased average real wage, surprisingly little is known about the impact of trade on the average real industrial wage from the viewpoint of aggregate productivity dynamics. Accordingly, the main question that this paper investigates empirically, using U.S. data, is as follows: under which labor market conditions does trade raise the average real industrial wage?

Recent theoretical attempts to employ worker heterogeneity in international trade models help to identify labor market conditions due to explaining firms' and workers' heterogeneous responses to trade. Davidson, Matusz, and Shevchenko (2008) show, as the economy becomes more open to trade, how high ability workers in non-exporting firms respond to exporting firms' better offers relative to non-exporting firms. Additionally, Helpman, Itskhoki, and Redding (2009) explain why firms, under trade liberalization, screen and fire workers with ability below the cut-

[2] Archarya and Keller (2008) and Melitz and Ottaviano (2008) consider product market competition as an alternative mechanism to cause the selection effect.

off, and further how firms and workers share the firm's profit according to abilities.[3] These studies imply that the compensation for a worker's ability could be the worker's and firm's most important criterion for making economic decisions. However, though, how can we handle the question of worker heterogeneity, with respect to abilities, in an empirical study? Generally, econometricians cannot observe a worker's heterogeneous abilities directly. As a result there is little empirical evidence despite some theoretical attempts. In this situation, a good alternative is the residual wage stemming from the Mincerian wage equation, because the residual wage reflects the compensation for a worker's ability.[4]

To understand the relationship between abilities and the residual wage, this paper introduces worker heterogeneity with respect to abilities into Blanchflower, Oswald, and Sanfey's (1996) rent-sharing framework. According to this model, the residual wage is determined by a firm's profit and by individual bargaining power that comes from abilities;[5] that is, it reflects the compensation for workers' abilities, as evaluated by a firm. Therefore, although we cannot observe workers' abilities empirically, the residual wage enables us to estimate heterogeneous responses of firms and workers to changes in the compensation for workers' abilities.

[3] Here, the concept of ability in the above theoretical papers implies unobserved skills more than observed skills such as education and experience.

[4] Mincerian wage equation is used to estimate the premium of observed skills such as education and experience. The residual wage is empirically defined by the residual term in Mincerian wage equation. Therefore, it is likely to be connected to unobserved skills that affect the wage. Although the more popular term in studies on residual wage is unobserved skills, this paper uses ability instead of unobserved skills in order to link with theoretical studies on worker heterogeneity.

[5] This is similar to Lemieux (2006)'s assumption that residual wage is the product of abilities and compensation for them because firm's profit is related with firm's ability of compensating for unobserved skills.

Particularly, provided that firms' profits and productivities are identified, ability cut-offs in firms can be compared to each other.[6]

How can the residual wage explain the firm's decision to fire and hire workers? When a firm is faced with decreasing profit, it will lay off workers with low residual wages because those workers are evaluated as being less valuable by the firm. In other words, the residual wage reflects how the firm sorts its workers in terms of their performance. Also, in hiring workers to respond to increased market share, the firm will attempt to screen job applicants with abilities below the cut-off.[7] In the context of a worker's decision, the residual wage implies that workers with the same education level and experience could be paid differently according to the firm's profit, which helps explain the worker's motivation to search for a better job. If high-ability workers are in an unproductive firm, they will have the motivation to move toward a more productive firm in order to earn more compensation through individual bargaining. As a result, in a rent-sharing framework, the firm's and worker's decisions respond to changes in the firm's profit, which causes job flow.[8]

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[6] Firms with high productivity can cover huge recruiting cost to hire high-ability workers, while unproductive firms cannot afford to pay high recruiting cost. Therefore, unproductive firms are more likely to hire workers with low abilities than firms with high productivity because the adverse effect could be in unproductive firm's recruiting process. Therefore, this paper assumes that the cut-off is closely related to firm's productivity as suggested in Helpman, Itskhoki, and Redding (2009).

[7] According to Huang and Cappelli (2006), firms can evaluate job applicants' abilities by using popular screening practices such as reference letters and obtaining the agent's past histories through credit bureaus or hiring detectives.

[8] Krueger and Summers (1988) and Gibbson and Katz (1992) focus on the reallocation of workers from low to high wages industries; that is, they examine why workers with the same education level and experience are paid differently in different industries. The residual in this paper explains why the workers move from unproductive firms to more productive firms in the same industry as well as across industries.

Trade liberalization affects firms' profits according to their productivity (Melitz, 2003). Thus, as the economy becomes more open to trade, firms and workers make heterogeneous responses to the changes in the profit, which determines the average residual wage at the industrial level. These responses suggest two main channels through which trade affects the average residual industrial wage: both the change in the firm's profitability, and job flow. Without considering job flow, the influence on the residual wages of the change in a firm's profit from trade is obvious: imports lower the workers' residual wages because imports make the firm's market share shrink. In a similar way, exports raise the workers' residual wages.

However, taking job flow into consideration, the impact of trade on the average residual wage is more complicated. In the case of exports, the direction of each channel's impact is positive. With higher exports, exporting firms can make better offers to both inside and outside workers. Therefore, the workers who are compensated less relative to high abilities have the motivation to move toward exporting firms voluntarily due to the increased chances of obtaining a better job;[9] that is, the impact of job flow would depend on the magnitude of job creation in exporting firms. In sum, the impact of exports on the average residual wage is positive, and the residual wage becomes more dispersed, and left-skewed, the more job creation in exporting firms is working actively.

[9] Davidson, Matusz, and Shevchenko (2008) also argues that as the salary gap between exporting and non-exporting firms is widen due to increased exports, the workers with high ability have more motivation to move toward exporting firms.

On the other hand, the impact of imports on the residual wage distribution depends on the relative magnitude of the profit and job flow channels. Through a firm's profit, imports lower the residual wages. However, we must also consider the job flow channel. Increased imports also cause the marginal workers in firms, and the workers in marginal firms, to exit the market.[10] The effect of this job destruction is to raise the average residual wage at the industry level. That is, the directions of the two channels' effects are opposite. Therefore, there is still the possibility of removing the negative effect of import on the average (residual) wage without controlling for job destruction.[11] Unlike exports, with imports, the higher the job destruction, the less the residual wage is dispersed.

For empirical analysis, I use four datasets: Merged Outgoing Rotation Groups Current Population Survey (MORG-CPS), U.S. Trade by Feenstra (1998), Job Creation and Job Destruction by Foster, Haltiwanger, and Kim (2006), and Manufacturing Industry Productivity Database by Bartelsman, Becker, and Gray (2000).[12] The MORG-CPS provides me with a huge dataset as well as a less noisy

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[10] The case of marginal workers is similar to the cleansing effect in recession (Barlevy, 2000).

[11] Revenga (1992) summarizes and criticizes the early literatures which show insignificant or small impact of imports on the wage and employment (for example, Mann (1988), Grossman (1987)). In addition, Leamer and Levinsohn (1995) point out that Grossman (1987)'s methodology lacks treatment of cross-industry effects in estimating import price elasticity. However, due to job flow, there is the possibility of the positive relationship between imports and the average (residual) wage. This can be connected to the results in Ebenstein, Harrison, McMillan and Phillips (2009). They examine why the impact of import penetration on wages is empirically small despite having a relatively large impact on employment. They attempt to calculate occupation-specific import penetration in order to control for job destruction. By using it, they find a significant, negative, and sizeable impact of import penetration on individual wages.

[12] While investigating the relationship between manufacturing wages and international trade, Gaston and Trefler (1994) use the CPS in order to reflect the characteristics of individual workers in the industry. Recently, Ebenstein, Harrison, McMillan and Phillips (2009) and Liu and Trefler (2008) have attempted to link industry-level data on offshoring activies of U.S. multinational firms, import penetration, and export shares with the CPS.

measure of the key variable of interest (compensation per hour) relative to March CPS or PSID (Lemieux, 2006). This is important because this paper restricts the sample to full-time male workers in the manufacturing sector and obtains the residual wage from hourly wages by using the Mincerian wage equation. The dependent variables are the average and 10th percentile of estimated residual wage. Those dependent variables and explanatory variables such as job flow enable us to understand how the residual wage distribution is changed by trade, and to examine the labor market conditions under which trade raises the average residual wage at the industry level.

Since it is difficult to measure trade liberalization by changes in policy, the typical approach is to use trade openness, transaction costs, tariffs and so forth as proxies for trade liberalization. Alternatively, this paper attempts to capture trade liberalization by using import penetration, export propensity, and the real industrial shipment.[13] Particularly, the real industrial shipment controls for other factors such as changes in consumer's taste and technology. Furthermore, this paper uses U.S import weighted average tariffs as a robustness check in measuring trade liberalization.

This paper employs a dynamic panel model in order to reflect the persistence of residual wage distribution.[14] According to Cameron and Trivedi (2005), the within estimator cannot sufficiently control for the endogeneity problems induced

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[13] Import penetration is the share of import in domestic consumption *i.e.* (imports)/(shipment+imports-exports). Export propensity is also the share of exports in domestic production *i.e.* (exports)/(shipment+imports-exports).

[14] Since some interviewers in MORG-CPS can be observed between two years, the variables of interest are likely to be persistent.

by the use of the lagged dependent variable as the explanatory variable, the measurement error arising in pseudo panel and the issue of reverse causality. In order to avoid these endogeneity problems, I employ the system GMM (General Method of Moments) estimator proposed by Blundell and Bond (1998). In particular, I use Bowsher's (2002) suggestion and the standard error correction by Windmeijer (2005) in order to avoid overfitting bias and the small sample bias, respectively.

I find that the import penetration lowers the average residual wage, but the export propensity raises the average residual wage. The impact of import penetration especially depends on the level of job destruction, while that of export propensity depends on the level of job creation. When much job destruction occurs, the impact of import penetration on the average residual wage changes toward being positive. This interesting result is also supported by the evidence from the 10^{th} percentile regression. Particularly, the regression of the 10^{th} percentile of residual wage on job destruction shows that the left-tail of the residual wage distribution will be cut off as more job destruction occurs.

In addition, as job creation increases, the impact of export propensity on average residual wage is more positively sizeable. This result is predicted in Davidson, Matusz, and Shevchenko (2008) and Helpman, Itskhoki, and Redding (2008); that is, in response to increased exports, exporting firms hire workers with abilities above the cut-off rather than the unemployed. Therefore, despite job creation induced by exporters, workers with abilities below the cut-off are still likely to be unemployed.

In sum, this paper shows that with high union density, low job destruction, and low job creation, the effect of trade on average residual wage is likely to be negative. This is because without active job flow, the imports' negative impact on residual wages exceeds the exports' positive impact on residual wages; that is, trade liberalization is likely to be negatively associated with average residual wage in the more rigid labor market. In addition, this paper attempts to check the robustness of those results by measuring trade liberalization as the degree of tariff, finding consistent results.

Moreover, to link those results with the impact of trade on average real industrial wage, this paper runs the regression of the predicted average wage on import penetration and export propensity.[15] According to the results, trade is shown to have an insignificant impact. This result is anticipated by the fact that the Mincerian wage equation does not reflect industrial characteristics. As a result, the impact of trade on the average industrial wage is determined only by the residual wage. Consequently, since trade liberalization in the more rigid labor market does not increase the average industrial wage, the selection effect is unlikely to occur and so worker's welfare under those conditions will not be raised in the long-run.

The rest of the paper is organized as follows. In Section 2, I show the conceptual framework in order to understand how worker and firm make their decision according to residual wage. I present a description of the dataset and the estimation strategy in Section 3. Section 4 contains the results from regressions of

[15] The average real wage can be decomposed into the predicted average wage and the residual average wage.

several dependent variables on import penetration, export propensity, job flow, etc. Section 5 shows the result of robustness checks. Section 6 concludes.

I.2 An Illustrative Model

The purpose of this section is to explain i) how the residual wage is determined and ii) how trade affects the average residual wage at the industry level through what channels. For this, I modify the model in Blanchflower, Oswald, and Sanfey (1996) by making the worker's bargaining power dependent on his/her ability, and by employing the production function used in Helpman, Itskhoki, and Redding (2008).[16] This model is straightforward and useful in deriving implications for estimation.

Helpman, Itskhoki, and Redding (2008) effectively use the following production function to describe why the firm attempts to screen workers with abilities below the cut-off:

$$y = \theta h^{\gamma} \bar{a}, \; 0 < \gamma < 1,$$

where θ is firm's productivity, h is labor supply, a_i is worker i's ability, and $\bar{a}$ is the average of workers' ability in a firm. Worker ability (a_i) and firm productivity (θ) are assumed to be drawn from a Pareto distribution, with cumulative

[16] Blanchflower, Oswald, and Sanfey (1996) explain the positive relationship between profit and wage. This rent-sharing model is relevant in U.S. manufacturing because Estevao and Tevlin (2003) find a substantial amount of rent sharing. In particular, Cunat and Guadalupe (2009) show that import penetration affects the compensation structure through changing the sensitivity of pay to performance in their sample of U.S. executives.

distribution function, $G_a(a) = 1-(a_{\min}/a)^k$ for $a \geq a_{\min} > 0$ and $k > 2$ and $G_\theta(\theta) = 1-(\theta_{\min}/\theta)^z$ for $\theta \geq \theta_{\min} > 0$ and $z > 2$, $k > 2$, respectively.

Thus, this production function depends upon the productivity of the firm (θ), the average of abilities in a firm ($\bar{a}$), and the number of workers hired (h). The including average ability in the production function gives the firm a motive to screen out workers with abilities below the cut-off. If the firm fires the workers with abilities below the cut-off, the effect of increased average ability in a firm could exceed the effect of the decreased number of workers. With a Pareto distribution of worker abilities, the average ability in a firm is given by $\bar{a} = ka_c/(k-1)$. Since the average ability level of the workers in a firm is dependent on a screening cut-off a_c, the firm will determine this cut-off based on the screening costs it must pay.

This paper also uses screening costs as modeled in Helpman, Itskhoki, and Redding (2008). It assumes that if the firm pays a screening cost of ca_c^δ/δ, it can screen the workers with abilities below a_c inside and outside of the firm. Since the firm needs costlier tests for higher ability cutoffs, screening costs are an increasing function of ability cutoff, a_c, chosen by the firm. Therefore, we can conceptualize setting the cut-off as directly related to the firm's productivity. The firm also confronts other costs. Production involves a fixed production cost of f_d. For serving the foreign market, the firm incurs a fixed exporting cost of f_x and variable trade costs. Particularly, this variable trade cost takes the iceberg form, such that $\tau > 1$ units of a variety must be shipped in order for one unit to arrive in the other country.

Having defined the production function and associated costs, we can now build the profit function, $\pi = (1 - I_x \tau) py - \sum_{i=c}^{h+c} w_i - \frac{c}{\delta} a_c^{\delta} - f_d - I_x f_x$. We can also define the bargaining model through which wage is determined. Worker's utility is assumed to be a function of individual wage. Therefore, in the bargaining model where the firm and its individual employee negotiate wage and employment status, the maximization problem is as follows:

$$Max \sum_{i=c}^{h+c} \phi(a_i) \log(u(w_i) - u(\overline{w})) + (1 - \sum_{i=c}^{h+c} \phi(a_i)) \log \pi \qquad (1)$$

where $u(w_i)$ is worker i's utility from wage w_i and $\overline{w}$ is the wage available to the worker by obtaining temporary work in the event of a breakdown in bargaining. Since temporary work does not reflect returns to ability, $\overline{w}$ can be interpreted as general compensation for education and experience in the economy. ϕ is the bargaining power of an employee. Here, the bargaining power is determined by the worker's ability, a_i, because the firm takes longer to replace a high ability worker, and the firm is likely to earn zero in the event of a bargaining delay. Although the above maximization problem has three choice variables, h, a_c, and w_i, this paper derives the first-order condition with respect to w_i because the introduction of worker heterogeneity makes the optimization problem more complicated when maximization is with respect to h and a_c. Furthermore, the first-order condition with respect to w_i is sufficient to explain how the residual wage is determined and thereby construct the estimation equation.

At an interior optimum, the following first-order condition with respect w_i holds:

$$w_i: \frac{\phi(a_i)u'(w_i)}{[u(w_i)-u(\overline{w})]} - \frac{1-\sum_{i=c}^{h+c}\phi(a_i)}{\pi} = 0 \tag{2}$$

Rewriting the first of these, we obtain

$$\frac{u(w_i)-u(\overline{w})}{u'(w_i)} = \left(\frac{\phi(a_i)}{1-\sum_{i=c}^{h+c}\phi(a_i)}\right)\pi \tag{3}$$

which can be simplified by using $u(\overline{w}) \cong u(w_i) + (\overline{w} - w_i)u'(w_i)$ to produce the equilibrium residual wage as follows:

$$w_i - \overline{w} \cong \left(\frac{\phi(a_i)}{1-\sum_{i=c}^{h+c}\phi(a_i)}\right)\pi\ . \tag{4}$$

Equation (4) is useful for understanding how the residual wage is determined. It shows that, to a first-order approximation, the equilibrium residual wage is determined by profit and the relative bargaining strength between the firm and its individual employee, according to an employee's ability; that is, it reflects the compensation for workers' abilities, as evaluated by the firm. This is similar to Lemieux (2006)'s interpretation that the residual wage is the product of abilities with the return to abilities. Therefore, the residual wage implies that workers with the same education level and experience may be paid differently according to the firm's productivity or profit. Moreover, workers with the same education level and experience in the same firm may be paid differently according to their performance.

From equation (4), we know that profit and bargaining power affect the slope in the relationship between the residual wage and abilities. Therefore, we can set up the schedule of the residual wage to abilities in an exporting firm and a non-exporting firm. <Figure 1> shows these schedules in an environment characterized by a low degree of openness:

<<Figure 1>>

a_c^n is the cut-off point for a non-exporting firm; if a worker has abilities less than the cut-off, the worker is unemployable. The returns to high ability workers will be higher in both an exporting and a non-exporting firm. The difference between the two slopes implies that an exporting firm can make more profit and better offers. When there is a low degree of openness, the difference in the two slopes is not large. In this case, the workers ($a > a_c^n$) in a non-exporting firm have less motivation to move toward an exporting firm.[17]

Additionally, an exporting firm will invest more, relative to a non-exporter, in a screening mechanism to identify workers with abilities below the cut-off, in order to retain high ability inside workers, and to obtain high ability outside workers. That is, due to paying additional costs such as the exporting fixed cost and transportation cost, an exporting firm should be more productive, and hence need

[17] This is similar to "Cross-Skill Matching" equilibrium. Davidson, Matusz, and Shevchenko (2008) defines it as one in which high-skill workers are willing to accept low-tech jobs. Additionally, they define an "Ex-Post Segmentation" equilibrium as one in which skilled workers are not willing to do so.

workers with high abilities. Therefore, the cut-off point of an exporting firm, a_c^e, is higher than that of a non-exporting firm.

Through <Figure 2>, we can discern how the distribution of residual wage changes as the economy becomes more open to trade. A higher degree of trade openness in a country where intra-industry trade dominates implies higher import penetration and higher export propensity in the same industry. First, the impact of increased import penetration on residual wages is shown by arrows (1) and (2) in <Figure 2>. When import penetration increases, the higher competition in the domestic market requires a non-exporting firm to have workers with higher abilities. Thus, the cut-off for a non-exporting firm increases by $\overline{a_c^n}$.[18] Consequently, workers with abilities below the new cut-off and workers in marginal firms will be unemployed. This effect of increased imports (arrow (2)) raises the average residual wage as <Figure 2>. However, there is another effect of increased imports (arrow (1)). Import penetration also makes the curve of non-exporting firms shift downward because the reduced domestic market share causes decreasing profit. Therefore, the impact of increased imports on the average residual wage depends on the relative magnitude of the two effects; that is, when job destruction below the new cut-off ($\overline{a_c^n}$) occurs more, the effect of the shifting downward curve on the average residual wage is decreased.

<<Figure 2>>

[18] In a different way, increased import penetration pushes up the cut-off for a non-exporting firm productivity (θ). Therefore, since surviving non-exporting firms are likely to have a higher screening cut-off, the new cut-off ($\overline{a_c^n}$) is higher than a_c^n.

Furthermore, arrows (3) and (4) represent the influence of increased export propensity. A higher degree of trade openness implies that the existing exporters can sell more abroad, and some non-exporting firms can start to export, which causes increases in exporting firms' profits and labor demand. Therefore, an exporting firm's slope shifts outward (arrow (3)) and the cut-off of an exporting firm lowers, because the decrease in export costs enables a non-exporting firm with a cutoff slightly below that of an exporter to join the foreign markets (arrow (4)). In particular, the gap between an exporter's slope and a non-exporter's slope is widening. As a result, workers with ability above $\overline{a_c^e}$ in exporting firms have more motivation to move toward exporting firms because of higher compensation for their ability.[19] At this point, the key point is that job creation in incumbent and newly exporting firms accelerates this process. This implies that exporting firms are likely to search for workers with abilities above the cut-off in the pool of the employed rather than the pool of the unemployed.[20] As job creation in exporting firms increases, the impact of exports on the residual wage also increases.

The implications derived from this conceptual framework shed an important light on our construction of the estimation model in Section 3 and interpretation of the results of regressions in Section 4.

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[19] This implies that the economy moves from a "Cross-Skill Matching" equilibrium to an "Ex-Post Segmentation" in Davidson, Matusz, and Shevchenko (2008).

[20] Menezes Filho and Muendler (2007) show the interesting evidence that tariff cuts and additional imports trigger worker displacements, but that neither comparative-advantage sectors nor exports absorb trade-displaced worker. This evidence implies that an exporting firm searches its workers in the pool of employed, rather than unemployed.

I.3 Data and Estimation Strategy

Data Description

The best way to examine the impact of job flow induced by trade on the average residual wage, as described in section II is to use a matched employee-employer dataset. However, generally speaking, these matched employee-employer datasets are not made publicly available. To answer the main question empirically then, I combine several data sets: Merged Outgoing Rotation Groups Current Population Survey (MORG-CPS), U.S. Trade by Feenstra (1998), Job Creation and Destruction by Foster, Haltiwanger, and Kim (2006), and Manufacturing Industry Productivity Database by Bartelsman, Becker, and Gray (2000).

The CPS is a monthly household survey conducted by the Bureau of Labor Statistics to gather information on the labor force characteristics of the U.S. population. According to Cameron and Trivedi (2005), households are interviewed in four consecutive months, ignored for eight months, and then interviewed again for another four months. The CPS-MORG consists of households in their 4th and 8th interview. Lemieux (2006) shows that this data is more reliable than alternative sources of wage data, such as March CPS, because it provides a less noisy measure of the key variable of interest, compensation per hour. In addition, the CPS-MORG has a larger number of observations than PSID or March/May CPS.[21] This feature is important in enabling me to restrict the sample to full-time male workers aged 16

[21] The MORG supplement is roughly three times as large as the May or March supplements of the CPS.

to 64 in the manufacturing sector. This paper also divides the industry using a narrower classification, thereby obtaining 74 categories of industry.[22] This narrower classification would be difficult without the large number of observations provided by the CPS-MORG.

For information on wage, I use hourly wages as reported in the CPS-MORG because theories of wage determination are closely connected with the hourly wage rate.[23] Real hourly wage is calculated by using the Consumer Price Index (CPI). As in Lemieux (2006), I trim extreme values of wages (less than $1 and more than $100 in 1979 dollars) and weight wage observations using the CPS weights. In addition, top-coded weekly and hourly wages are multiplied by a factor of 1.4.[24] I draw the distribution of real hourly wage for full-time male workers in the manufacturing sector in both 1983 and 1994 using the kernel density method. Panel (a) in <Figure 3> shows that the hourly real wage in 1994 is more dispersed than in 1983, as suggested in many studies on inequality of real hourly wage.

Information on observable skills such as education and experience is required to obtain the residual wage. When using schooling as a regressor in wage

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[22] CPS has its own industry classification based on SIC code. There are some sectors which cannot be divided by SIC87 3-digit. So I merge them; that is, primary aluminum industry and other primary metal industry are merged; scientific and controlling instruments industry and medical, dental, and optical instrumental and supplies industry are also merged. And, I exclude leather tanning and finishing industry and watches, clocks and clockwork operated devices industry because the observations is not enough. However, as compared with early literatures, this industry classification is very narrow and heterogeneous in terms of cross-section. For example, Revenga (1992) use 38 three- and four-digit SIC (narrower, wage, employment also negative).

[23] If hourly wage were absent and only weekly wages were recorded, it would be defined as weekly wages divided by usual weekly hours for salaried workers.

[24] There are several ways to control top-coded weekly and hourly wage. DiNardo, Fortin, and Lemieux (1996) use the upper tail of the 1986 distribution of wages to impute a wage distribution to the observations censored at the top-code in other years. Also, according to the CPS questionnaire, it recommends them to be removed.

equations, the CPS has the well-known problem that schooling is not measured using a consistent questionnaire over time; that is, after 1992, a question about the highest graduate attended switched to the highest grade or diploma completed, instead of asking whether the highest grade was completed. Nonetheless, Lemieux (2006) suggests a possible way to construct a relatively consistent variable for years of schooling completed over the whole sample period. In his manner, this paper classifies years of schooling completed into nine groups: 0-4, 5-8, 9, 10, 11, 12, 13-15, 16, and 17+. Also, experience is measured by a proxy variable, age.

Additionally, from the CPS-MORG, I obtain the union density rate across industries in order to reflect labor market conditions. Other indexes utilized in this paper are import penetration and export propensity from Feenstra (1998), job destruction and job creation from Foster, Haltiwanger, and Kim (2006), and real shipments from Bartelsman, Becker, and Gray (2000). These indices are measured by SIC 4-digit, so I match them into the CPS industry classification based on SIC 3-digit.[25] Since information on unions in the MORG-CPS only exists after 1983, and Feenstra provides us with a trade index up until 1994, the sample period in this paper is from 1983 to 1994.

The real hourly wage, education, and experience variables enable estimation of the residual wage. In the sample of full-time male workers in the manufacturing sector, the residuals come from separate regressions of the logarithm of real hourly

[25] In matching trade index and job flow index, I use output and employment in Bartelsman, Becker, and Gray (2000) dataset as weights.

wages on age, a quadratic in age, and nine schooling dummies for each year.[26] <Table 1> contains the estimation result of the Mincerian wage equation. The row of Stdev, the standard deviation of coefficients of eight schooling dummies, shows that the inequality among premiums on years of schooling is increasing. Particularly, the last row implies that the college premium is also increasing, coinciding with results in early literature.[27] In addition, panel (b) in <Figure 3> shows the distribution of full time male workers' residual wages in both 1983 and 1994. Similar to panel (a) in <Figure 3>, the distribution in 1994 is more dispersed.

Furthermore, I draw the cumulative distribution functions for residual wages in several industries in order to capture the impact of import penetration in industries with different labor market conditions. <Figure 4> and <Figure5> show the cumulative distribution functions of residual wages in industries with high rates of change in import penetration. However, the industries in <Figure 4> have high rates of change in job destruction, while the industries in <Figure 5> are characterized as having low rates of change in job destruction.[28] Compared with <Figure 4>, the 1994 residual wage distributions in <Figure 5> are located wholly to the left of 1983 residual wage distributions. Additionally, the 1994 cumulative

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[26] Lemieux (2006) uses the interactions between schooling dummies and a quadratic in age in order to improve R^2. This paper does not use interactions in order to emphasize that residual wages imply differences within a group with the same education and experience.

[27] Here, the college premium is calculated by subtracting the coefficient of ed6 from that of ed8. Since ed7 is 13-15 years of schooling completed, it is not relevant for college premium. Therefore, the paper assumes that 16 years of schooling is the bachelor degree. The college premium is the difference of wage between graduates from high school and ones from college.

[28] The logging industry and the office and accounting machines industry in <Figure 4> are amongst the top five industries for change rate of job turnover. Although the job turnover reflects the labor market rigidity well, however, I use the job destruction index in order to connect them with <Figure 2>.

distribution functions in <Figure 5> have a longer left-tail than the 1983 ones. This evidence provides suggestive support for the role of arrow (1) and arrow (2) in <Figure 2>. As a result, we can infer that a high change rate of job destruction enables an industry exposed to highly increased imports to have fewer workers with low residual wage. Additionally, <Table 2> reports the minimum, average, and maximum values of variables in order to calculate the marginal effects.

Estimation Strategy

This paper introduces the dependent variables average, and 10th percentile, of estimated residual wages at the industry level.[29] These dependent variables enable us to capture the response of residual wage distribution characteristics to trade. Equation (5) is the starting point in order to capture the impact of imports and exports on the residual wage.

$$Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 uni_{s,t} + \beta_3 \ln imp_{s,t} + \beta_4 \ln \exp_{s,t} + \beta_5 \ln rship_{s,t} + \varepsilon_{s,t} \quad (5)$$

where $Rw_{s,t}$ is the average, or 10th percentile, of the residual wage in industry s at time t; $uni_{s,t}$ is the union density of industry s at time t; $\ln imp_{s,t}$ is the logarithm of the import penetration ratio for industry s at time t; $\ln \exp_{s,t}$ is the logarithm of the export propensity ratio for industry s at time t; $\ln rship_{s,t}$ is the logarithm of real shipments in industry s at time t; $\varepsilon_{s,t}$ consists of the s industry-specific effect (ν_s),

[29] This strategy has an advantage to avoid the Moulton problem. If we construct the estimation equation with individual-level dependent variable and industry-level independent variables, the Moulton problem would make the standard errors underestimated. According to Angrist and Pischke (2009), using group averages instead of microdata is a good way to avoid the Moulton problem.

the time-specific effect (δ_t), and the error-term ($\eta_{s,t}$). In particular, the logarithm of real shipments controls for third factors such as changes in consumer's taste and technology. Therefore, the addition of real industrial shipments enables trade openness in this empirical model to be more closely connected with trade liberalization, as in Melitz (2003).

To answer the main question in this paper, however, I need to modify equation (5). From comparison of <Figure 4> with <Figure 5>, we can discern that the distributional consequence of import penetration on individual residual wages is dependent on the level of job destruction. This yields intuition as to how to construct the empirical equations in order to identify the role of each arrow in <Figure 2>. To reflect this intuition, I modify equation (5) to yield equations (6)-(8) by adding interaction terms with union density, job destruction and job creation, respectively. However, while running the regression of the 10th percentile of residual wage, I use equations (5)-(7) to identify the arrow (2) in <Figure 2>.

$$Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 uni_{s,t} + \beta_3 \ln imp_{s,t} + \beta_4 [\ln imp_{s,t} \times uni_{s,t}] + \beta_5 \ln \exp_{s,t} + \beta_6 [\ln \exp_{s,t} \times uni_{s,t}] + \beta_7 \ln rship_{s,t} + \varepsilon_{s,t} \qquad (6)$$

$$Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 neg_{s,t} + \beta_3 \ln imp_{s,t} + \beta_4 [\ln imp_{s,t} \times neg_{s,t}] + \beta_5 \ln \exp_{s,t} + \beta_6 \ln rship_{s,t} + \varepsilon_{s,t} \qquad (7)$$

$$Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 pos_{s,t} + \beta_3 \ln imp_{s,t} + \beta_4 \ln \exp_{s,t} + \beta_5 [\ln \exp_{s,t} \times pos_{s,t}] + \beta_6 \ln rship_{s,t} + \varepsilon_{s,t} \qquad (8)$$

where $neg_{s,t}$ is job destruction in industry s at time t; $pos_{s,t}$ is job creation in industry s at time t.

Although the CPS is a repeated cross-section, I can construct industry-level panel data in order to estimate equations (5)-(8). However, the MORG-CPS consists of households in their 4th and 8th interview. As a result, some interviewers are likely to be observed between two years. Since this makes the sample persistent, I use dynamic panel analysis. However, the dynamic model permits regressors to include lagged dependent variables, which causes an endogeneity problem.[30] Moreover, the reverse causality between the residual wage and job flow in the equation may occur; that is, the increase of residual wage in exporting firms causes high-ability workers in non-exporting firms to move toward exporting firms voluntarily, which affects job destruction positively. This also engenders an endogeneity problem. Additionally, according to Cameron and Triviedi (2005), measurement error induces the endogeneity problem in the case of building industry-level panel data using an individual-level data set.

The endogeneity problems presented above suggest use of the system GMM estimator. The main strength of this estimator is to provide more consistent and efficient estimates in the presence of endogeneity problems.[31] The system GMM estimator is proposed by Blundell and Bond (1998) in order to overcome a significant shortcoming of the first-difference GMM estimator by Arellano and Bond (1991). According to Blundell and Bond, the instruments used with the first-difference GMM estimator become less informative in models where the variance of

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[30] The fixed effects estimates of the lagged dependent variable can be severely biased downwards for small T as Nickell (1981) shows.

[31] Collado (1997) suggests the GMM estimator in order to address the endogeneity problem induced by the measurement error in Pseudo-panel. The sample used in this paper has the characteristics of a pseudo-panel due to aggregating the individual observations by year and industry.

the fixed effects is high relative to the variance of the transitory shocks. This engenders biased coefficients, and furthermore this problem becomes worse in a small sample. However, the system GMM estimator is expected to have much smaller finite sample bias due to combining in a system the first-differenced with the same equation expressed in levels.[32] Especially, this paper uses the standard error adjusted by the Windmeijer (2005) finite sample correction in order to reduce finite sample bias.

As the system GMM estimator is not a panacea, two necessary criteria and one possible problem should be noted. First, the system GMM estimator must satisfy two criteria: the test for serial correlation in the first-differenced errors and the Sargan test for overidentifying restrictions. Since a system has first-differences, the first test is to check whether serial correlation exists among the error terms, as proposed by Arellano and Bond (1991). The other, the Sargan test, evaluates whether instruments in this paper are valid. This could suffer from the problem that should be noted.

One possible problem stems from using all the available moment conditions, which is referred to overfitting bias. Bowsher (2002) shows that the use of too many instruments in GMM estimation causes the p-value of the Sargan test to be close to 1. This implies that the power of the Sargan test can be lost. To correct this problem, this paper restricts instrument sets by not using lags further back than $t-4$. This could improve the power of the test for overidentifying restrictions in

[32] According to Hayakawa (2007), the system GMM is less biased than the first difference and the level GMM estimator. Since the level GMM estimator has an upward bias and the difference GMM estimator has a downward bias, both biases cancel each other out in the system GMM.

spite of some loss of the efficiency of the estimates due to fewer instrument variables.

Therefore, I regard the system GMM as the preferred estimator. Since this data set aggregates the individual observation by year and industry, all reported standard errors and test statistics are heteroskedasticity-robust. In the case of the within estimator, I correct the standard errors by using a bootstrapping procedure.

I.4 Empirical Results

The empirical results are presented in <Table 3-4>. Each table presents the estimation results based on OLS (column 1), within estimation (column 2), and the system GMM (column 3-5) estimator. Also the first three columns in each table estimate equation (5) without the interaction term, while the next three columns estimate equations (6)-(8) with the interaction. As mentioned above, I will interpret the estimation results based on the preferred estimator, the system GMM.

Before interpreting the results, this paper will evaluate the system GMM estimator in terms of the validity of instruments and the model specification. All three diagnostic statistics in <Table 3-6> are satisfactory; that is, the Sargan test does not reject the over-identification restrictions; the absence of first order serial correlation is rejected while the absence of second order serial correlation is not rejected. Additionally, I am also concerned with overfitting bias and finite sample bias for the system GMM estimator. To avoid overfitting bias, I do not use any lags dated further back than $t-4$, and so all tables in this paper obtain the Sargan test

P-value much smaller than 1. In the case of finite sample bias, Bond (2002) suggests a useful fact: since the OLS and within estimator are biased in opposite directions, the coefficients on the lagged dependent variable estimated by a consistent estimator should lie between the OLS and within estimates. All coefficients on the lagged dependent variable in <Table 3-4> using system GMM are in this interval. This implies that finite sample bias associated with weak instruments is not present. In particular, Windmeijer's (2005) corrected standard error reduces finite sample bias. Therefore, all coefficients estimated by system GMM are consistent without problems.

Looking at column 3 in <Table 3>, the first point to note is that increases in import penetration are associated with decreases in average residual wage, while increases in export propensity are associated with increases in average residual wage. Specifically, an import penetration elasticity of -0.011 in column 3 is significantly different from zero at the 10% level. Also the export propensity elasticity in column 3 is 0.016 and significantly different from zero at the 5% level. Moreover, the long-run effect of import penetration and export propensity are -0.044 (SE=0.024) and 0.064 (SE=0.027), respectively.[33] [34] That is, the export propensity elasticity is larger than the import penetration elasticity. If the volume of export is

[33] The long-run effect is calculated as follows: the long-run effect of an import penetration elasticity is $\beta_3/(1-\beta_1)$=-0.011/(1-0.755)=-0.044 in column 3; the long-run effect of an export propensity is 0.016/(1-0.755)=0.064. The standard errors in the long-run effect are computed by the Delta-method.

[34] Despite of significance of those coefficients, the size of the coefficient is somewhat small relative to Revenga (1992) with the import price elasticity of 0.06. A possible explanation is use of a different data set. Contrary to this paper, Revenga (1992) uses the quarterly import price for the index of import competition.

similar to that of imports, it implies that trade may raise the average residual wage.

However, the above implication depends on the labor market conditions as suggested in section II. Let's focus attention on column 4-6 in <Table 3a>. In column 4, my intention is to capture the role of the labor market by interacting union density with import penetration and export propensity, respectively. Column 4 in <Table 3a> shows that the interaction term between union density and import penetration is negative and statistically significant at the 10% level. This implies that union density could be the crucial channel through which increased imports affect the average residual wage. In order to shed additional light on the quantitative importance of union density, I calculate the partial derivates of import penetration, i.e. the marginal effect. The marginal effect of import penetration varies depending on the level of union density. To gauge the range of variation, I calculate the derivatives of import penetration at the minimum, median and maximum values of union density. These are presented respectively in <Table 3b>. According to the first column of <Table 3b>, the marginal effects of import penetration decrease, and even change from negative to positive, as union density declines. Interestingly, with high union density, the effect of trade on average residual wage is likely to be negative because the impact of imports exceeds that of exports.[35]

[35] When the union density has the maximum value, the import penetration elasticity is -0.024 and the export propensity elasticity is 0.011. Therefore, -0.024 + 0.011 = -0.013.

<Figure 2> dealt with in section II allows us to interpret this evidence more clearly. This evidence implies that if the union negatively affects the firm's decision to fire workers below the cut-off, the denser the union is in increased imports, the more the average residual wage is affected by the arrow (1) relative to the arrow (2) in <Figure 2>. The union tends to preserve jobs through wage concessions. Furthermore, when the union bargains with the firm instead of individual workers, the union is likely to prevent the firm from sorting the workers according to abilities; that is, the firm with a denser union is less able to fire the workers with abilities below the cut-off through sorting.[36] Therefore, the denser union dampens the effect of arrow (2) in <Figure 2>. As a result, higher union density in the industry with increased imports is likely to decrease the average residual wage.

Column 5 in <Table 3a> suggests more interesting evidence. Here, I use the index of job destruction in order to capture the impact of arrow (2) in <Figure 2> directly. The interaction term is positive and statistically significant at the 5% level, while import penetration is negative and statistically significant at the 1% level. This result corresponds well with <Figure 2>. Similar to the case of union density, I calculate the marginal effect of import penetration at the minimum, median and maximum values of job destruction. The first column in <Table 3c> shows the results. The marginal effects of import penetration increase and change from negative to positive as more job destruction occurs. That is, when increased imports remove the marginal firms and marginal workers from the market through

[36] The correlation between union density and job destruction is -0.115, while the correlation between union density and job creation is -0.260.

increasing the cut-off of productivity and abilities respectively, the effect of job destruction can offset the decrease in average residual wage induced by decreasing profits. This phenomenon is similar to the cleansing effect in the sense that the workers with abilities below the cut-off become unemployed. By comparing with the coefficient of export propensity, we can determine that the less job destruction happens, the more likely the effect of trade on average residual wage is to be negative, because the impact of imports exceeds that of exports.[37]

Additionally, column 6 in <Table 3a> shows that the impact of exports on the average residual wage also depends on labor market conditions. Increased exports raise the residual wages in exporting firms because of increased profit, as suggested in equation (4). Also, exporting firms attempt to hire more workers with abilities above the cut-off. The job creation in the industry with increased exports is likely to raise the average residual wage because exporting firms can make better offers than non-exporting firms. According to column 6 in <Table 3a>, the interaction term between exports and job creation is positive and statistically significant at the 10% level. This result agrees with the increase in average residual wage anticipated by the arrow (4) in <Figure 2>. Particularly, the second column in <Table 3c> implies that as job creation increases, the magnitude of the marginal effect of export propensity is increasing. The more job creation happens, the more likely the effect of

[37] When job destruction has the minimum value, the import penetration elasticity is -0.036. The export propensity elasticity in column 5 is 0.021. Therefore, -0.036 + 0.021 = -0.015.

trade on average residual wage is to be positive because the impact of exports dominates that of imports.[38]

The existence of this causal effect can be supported by analyzing the workers located in the lowest percentile of residual wage distribution. For this reason, this current paper pays more attention to the 10th percentile of residual wage distribution. <Table 4a> shows the regression results from the 10th percentile of residual wages. Interestingly, the results in <Table 4a> show a similar pattern to that of <Table 3a>. Specifically, the interaction term between import and job destruction in column 5 is positive and statistically significant at the 1% level, while $\ln import_{s,t}$ is negative and statistically significant at the same level. According to the marginal effect of import penetration reported in <Table 4b>, job destruction causes the sizable variation of this marginal effect. That is, job destruction plays a critical role in raising the 10th percentile of residual wage. If the selection effect of import penetration on the workers with ability below the cut-off exists, then the 10th percentile of residual wage would be raised by import penetration. Therefore, as more job destruction occurs, the left-tail of the residual wage distribution will be cut. This will push up the average residual wage.

In order to connect these pieces of evidence to Melitz (2003) argument, this paper has to examine the impact of trade on the average industrial wage, including the average predicted wage as well as residual wage. Therefore, I turn attention to the impact of trade on the average predicted wage. <Table 5> reports the results

[38] When job creation has the maximum value, the export propensity is 0.043. The import penetration elasticity in column 6 is -0.015. Therefore, 0.043 - 0.015 = 0.028.

from regressions of the average predicted wage on trade. According to column 3 in <Table 5>, import penetration and export propensity are statistically insignificant at the 10% level. We can anticipate this given the fact that the Mincerian wage equation does not reflect industrial characteristics. In sum, the impact of trade on the average industrial wage is determined only by the residual wage; that is, with high union density, low job destruction, and low job creation, the effect of trade on the average wage is likely to be negative. Therefore, trade liberalization in a more rigid labor market is unlikely to induce the selection effect and thus worker's welfare will not be raised in the long-run.

I.5 Robustness Check

To check the robustness of above results, this section employs the size of tariff as another way to measure trade liberalization. Specifically, in this section I examine the impact of U.S. import weighted average tariffs on the average and 10th percentile of residual wages, using the following equations:

$$Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 \ln rship_{s,t} + \beta_3 uni_{s,t} + \beta_4 \ln tariff_{s,t} + \varepsilon_{s,t} \qquad (9)$$

$$\begin{aligned} Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 \ln rship_{s,t} + \beta_3 pos_{s,t} + \beta_4 neg_{s,t} \\ + \beta_6[\ln tariff_{s,t} \times pos_{s,t}] + \beta_6[\ln tariff_{s,t} \times neg_{s,t}] + \varepsilon_{s,t} \end{aligned} \qquad (10)$$

where $\ln tariff_{s,t}$ is the logarithm of the tariff in industry s at time t.[39] However, in the 10th percentile regression, the job creation variables ($pos_{s,t}$ and [$\ln tariff_{s,t} \times pos_{s,t}$]) are excluded, because the 10th percentile regression is intended to identify the arrow (2) in <Figure 2>.

According to the results, the logarithm of tariffs is negatively but insignificantly associated with the average residual wage. One explanation for this lack of significance could be that the decreased tariffs are likely to cause increased imports and exports, and thus the impact of imports on the residual average wage could be offset by that of exports, and vice versa. However, column 2 in <Table 6a> and column 1 in <Table 6b> show that when job creation and job destruction are higher, the impact of tariffs on the residual wage is more sizable and significant.

The regression of 10th percentile of residual wages supports these results. Column 3 in <Table 6a> shows that the logarithm of the tariff negatively and significantly affects the 10th percentile of residual wages; that is, the lower the tariff is, the higher the 10th percentile of residual wage is. Furthermore, column 4 in <Table 6a> reports that the interaction term between tariff and job destruction is negative and statistically significant at the 5% level. This interaction term is depicted by the arrow (2) in <Figure 2>, which shows that active job destruction is the crucial channel through which trade liberalization, proxied by tariffs, affects the 10th percentile of residual wage. Specifically, my results show that the magnitude of the marginal effect of tariffs is increasing with job destruction. These results are

[39] The variable of tariff refers to U.S. import weighted tariffs (duties/custom value). Schott provides this dataset on his website (http://www.som.yale.edu/faculty/pks4/sub_international.htm).

consistent with the impact of trade openness on the average and 10^{th} percentile of residual wages.

I.5 Conclusion

Under which labor market conditions does trade raise the average real industrial wage? This paper shows that with low union density, high job destruction, and high job creation, trade would raise the average real industrial wage. In fact, job creation is closely related with job destruction. According to Scarpetta et al (2002), employment protection legislation (EPL) prevents new firms from entering the market because of higher firing costs. Job destruction and job creation are in fact just two sides of the same coin. That is, more job destruction can induce more job creation. Therefore, as trade is increasingly liberalized, job turnover is increasingly important in order to cause the selection effect of trade found in Melitz (2003).

This implication sheds new light on the study of trade and aggregate productivity. Melitz and Ottaviano (2008) and Archaya and Keller (2008) suggest that trade can lower aggregate productivity under unilateral trade and high entry barriers, respectively. In particular, the high entry barrier in Archaya and Keller (2008) can be connected to labor demand, i.e. the job creation. Therefore, as suggested in this paper, labor market conditions can be an important causal link; if rigidity in the labor market causes firms to incur high firing costs, trade will lower the average real industrial wage and the selection effect of trade found in Melitz

(2003) will never happen. As a result, the more trade increases, the more labor market conditions matter for aggregate industry productivity dynamics and for the long-run welfare of workers.

CHAPTER II

TRADE, JOB FLOWS AND AGGREGATE INDUSTRY PRODUCTIVITY IN U.S. MANUFACTURING

II.1 Introduction

This paper investigates empirically how job flows influences aggregate industrial productivity in the United States, as it becomes more open to trade. The United States has experienced with the coexistence of high import share and high export share within industry, i.e. the intra-industry trade pattern. This implies that although the increased import penetration threatens unproductive non-exporting plants, the increased export propensity in the same industry allows a greater chance for incumbent exporting plants to sell more abroad and for new exporting plants to enter a market. In the situation, the productivity gains from trade-liberalization could stem from the reallocation of domestic resources from unproductive plants toward more productive ones within industry as well as across industries. This makes us pay more attention on the selection effect of trade in Melitz (2003), which implies that the competition in labor market induced by trade liberalization removes the least productive plants from the market and boosts the aggregate industrial productivity. Consequently, this paper attempts to examine how job flow affects the selection effect of trade.

Recent trade theories tell us the substantial role of job flow in the selection effect process. Davidson, Matusz and Shevchenko (2008) consider job creation in exporting plants as the catalyst of the selection effect. They show that as trade liberalization widens the gap of wage between an exporting plant and a non-exporting plant, workers with high abilities in non-exporting plants have the greater motivation to move toward exporting plants, and therefore these transfers accelerates the selection effect of trade because non-exporting plants will be more unproductive. Accordingly, job creation can boost aggregate industrial productivity, as the economy becomes more open to trade.

Helpman, Itskhoki and Redding (2008) cast the crucial clue on the mechanism regarding the impact of job destruction on the selection effect of trade. By introducing the average of workers abilities in a firm into the production function, they attempt to explain the firm behavior of screening inside and outside workers with abilities below the cut-off after trade-liberalization. Trade liberalization makes non-exporters faced with the decreased domestic market share. To survive in this market, non-exporters attempt to downsize in order to have a higher chance of regaining productivity. In particular, in downsizing a plant, it is important that a plant can use flexibly the mechanism of sorting workers in terms of ability and screening workers with abilities below the cut-off. If this mechanism works well, job destruction can push up the aggregate industrial productivity.

Lastly, based on Melitz (2003), Kang (2010) shows that with low job destruction and job creation, the selection effect of trade is less likely to occur. According to Melitz (2003), the labor market can be the crucial channel through which trade liberalization increases aggregate industrial productivity. In his theoretical model, the increased industrial real average wage by trade liberalization triggers the selection effect of trade. The unproductive non-exporting firms cannot afford to pay it. Kang (2010) attempts to specify labor market conditions under which trade induce the increased real average wage, and concludes that with high union density, low job destruction, and low job creation, trade is likely to decrease the average real wage. That is, under these labor market conditions, the selection effect of trade may not exist, and even a negative selection effect may occur. As a result, this paper can hypothesize that high job destruction and high job creation would raise the aggregate industrial productivity, as the economy becomes more open to trade.

To test empirically the hypothesis, this paper employs four datasets: U.S. Trade by Feenstra (1998), Import Weighted Tariffs by Schott, Job Creation and Job Destruction by Foster, Haltiwanger, and Kim (2006), and Manufacturing Industry Productivity Database by Bartelsman, Becker, and Gray (2000). Since plant's total factor productivity (TFP) tends to be persistent, I employ the dynamic panel analysis. Using the system GMM estimator to isolate the effect of the exogenous component of each explanatory variable on TFP, I find that import penetration is significantly and positively associated with the industrial TFP in the 10% level, and furthermore this magnitude is dependent on the level of job destruction. Additionally, tariffs negatively but insignificantly affect the industrial TFP in the 10% level. However, the interaction term between job creation and tariffs is significant in the 10% level. So job creation can be considered as the channel which trade liberalization pushes up the aggregate industrial productivity.

The rest of the paper is organized as follow. In Section II, I explain the estimation strategy and dataset. Section III contains the results. Section IV concludes.

II.2 Estimation Strategy and Data

This paper estimates the effect of job flow on aggregate industrial productivity in trade liberalization. For model specification, it should note two facts. First, the relative differences in productivity between plants are persistent through time as shown in Bartelsman and Doms (2000). To allow for inertia of productivity, this paper employs the dynamic panel model. The other is the difficulty to measure trade liberalization. Basically, I use import penetration and export propensity in equation (1). This can reflect that import penetration is more related to job creation and export is related to job creation. As a result, equation (1) has the interaction term between import penetration and job destruction as well as that between export propensity and job creation.

$$\begin{aligned} \ln TFP_{s,t} &= \alpha + \beta_1 \ln TFP_{s,t-1} + \beta_2 \ln rship_{s,t} + \beta_3 pos_{s,t} + \beta_4 neg_{s,t} \\ &\quad + \beta_5 imp_{s,t} + \beta_6 [imp_{s,t} \times neg_{s,t}] + \beta_7 \exp_{s,t} + \beta_8 [\exp_{s,t} \times pos_{s,t}] + \varepsilon_{s,t} \end{aligned} \tag{1}$$

where $\ln TFP_{s,t}$ is the logarithm of total factor productivity (TFP) in the industry s at time t; $\ln rship_{s,t}$ is the logarithm of real shipment of industry s at time; $pos_{s,t}$ is the job creation of industry s at time t; $neg_{s,t}$ is the job destruction of industry s at time t; $imp_{s,t}$ is the import penetration ratio of industry s at time t; $\exp_{s,t}$ is the export propensity ratio of industry s at time t; $\varepsilon_{s,t}$ is consisted of the s industry-specific effect (ν_s), the time-specific effect (δ_t), and the error-term ($\eta_{s,t}$).

For robustness to measure trade liberalization, this paper also employs import-weighted tariff in equation (2).

$$\begin{aligned} \ln TFP_{s,t} &= \alpha + \beta_1 \ln TFP_{s,t-1} + \beta_2 \ln rship_{s,t} + \beta_3 pos_{s,t} + \beta_4 neg_{s,t} \\ &\quad + \beta_5 \ln tariff_{s,t} + \beta_6[\ln tariff_{s,t} \times neg_{s,t}] + \beta_7[\ln tariff_{s,t} \times pos_{s,t}] + \varepsilon_{s,t} \end{aligned} \tag{2}$$

where $\ln tariff_{s,t}$ is the logarithm of import-weighted tariff in the industry s at time t.

The dynamic panel analysis forces us to consider the potential endogeneity problem of explanatory variables. To remove this concern, this paper uses the system GMM estimator that combines moment conditions for the regression in differences with moment conditions for the regression in levels as suggested by Blundell and Bond (1998). Under the assumptions on the autoregressive structure of error term and weakly exogeneity of explanatory variables, this estimator can control industry-specific fixed effect and avoid the endogeneity problem by using internal instrument variables that are based on lagged values of the explanatory variables. Accordingly, the consistency of this estimator depends on whether lagged values of the explanatory variables are valid instruments. The Sargan/Hansen test of overidentifying restrictions can check it. Additionally, this paper will report the result of marginal effects to consider the inquiry of this paper precisely.

The estimation combines data from four sources: U.S. Trade by Feenstra (1998), Import Weighted Tariffs by Schott, Job Creation and Job Destruction by Foster, Haltiwanger, and Kim (2006), and Manufacturing Industry Productivity

Database by Bartelsman, Becker, and Gray (2000).[40] Specifically, Manufacturing Industry Productivity Database reports two kinds of annul industrial TFP level values between 1958 and 1996: a four-factor level (capital, production worker hours, nonproduction workers, and materials) and a five-factor level (materials are divided into nonenergy materials and energy). This paper uses a four-factor level because the two are extremely high correlated. The above datasets are overlapped in 391 4-digit SIC industries from 1974 to 1994.

II.3 Empirical Results

Before proceeding to the interpretation of the results in <Table 7>, we should check whether the specification tests generally support the system GMM estimator. In all cases, the Hansen test of overidentifying restrictions cannot reject the null hypothesis that the instruments are uncorrelated with the error term. The tests of serial correlation show that the error term is first-order serially correlated. These results support the validity of instruments and thus allow us to draw inferences regarding the link between the explanatory variables and TFP.

According to column 1 in <Table 7>, import penetration affects TFP positively and significantly in the 10% level, while export propensity is negatively and insignificant associated with TFP. Particularly, the interaction term between import penetration and job destruction in column 2 suggests that job destruction

[40] Schott provides this dataset on his website (http://www.som.yale.edu/faculty/pks4/sub_international.htm). The other datasets are provided by NBER website.

can be the crucial channel through which imports affect aggregate industrial productivity. The first column of <Table 8> indicates that the more job destruction occurs, the bigger the impact of import on TFP is.[41]

Column 3, 4 in <Table 7> show that the level of tariffs affects negatively and insignificantly TFP, and this influence is significantly dependent on job creation in the 5% level. According to <Table 9>, the marginal effect of tariffs is changed from positive to negative, which means that high job creation and destruction cause trade liberalization to push up the aggregate industrial productivity.

II.4 Concluding Remark

Since job flow results from firms' and workers' responses/adjustment to outer shocks, job creation and job destruction can affect the distribution of aggregate industrial productivity across existing employment relationship. This paper considers trade liberalization as one of outer shocks with which firms and workers are confronted. The findings in this paper indicate that job flow can be the crucial channel through which trade liberalization boosts the aggregate industrial productivity.

[41] When the value of job destruction is around 4.08, this marginal effect is zero.

CHAPTER III

TRADE, JOB FLOWS AND AGGREGATE INDUSTRY PRODUCTIVITY IN U.S. MANUFACTURING

III.1 Introduction

Integrated product markets potentially increase aggregate productivity through two main effects: the international R&D spillover effect and the selection effect.[42] Since the selection effect reallocates resources toward the more productive firms by driving out the least productive ones, this process could be hindered by rigidity in domestic labor market institutions. Although this suggests the role of labor market institutions in an open economy, little is known about the impact of labor market rigidity on the selection effect.[43] Therefore, this paper examines empirically how rigidity in domestic labor market institutions influences the selection effect as the economy becomes more open to trade.

The importance of this question arises from the possibility of negative selection effect. Recently, Melitz and Ottaviano (2008) suggest that under unilateral trade, there can be the negative selection effect that hurt aggregate productivity. Based on this paper, Archaya and Keller (2007) find the empirical evidence of

[42] In this paper, the selection effect implies the positive selection effect.

[43] The research on the impact of institutions on the international R&D spillover effect has been done by Coe, Helpman, and Hoffmaister (2009). They show that well-established institutions such as the ease of doing business, the quality of tertiary education, the strength of intellectual property rights, and the origins of legal system enhance the international spillover effect. However, they did not find significant evidence from financial market development, labor market institutions, governance, and ease of trading across borders.

negative selection effect in OECD countries, and furthermore conclude that foreign R&D spillover effect can be offset by the negative selection effect in the long run. These studies consider product market competition as the mechanism that causes the selection effect. Therefore, one can expect that if the product market regulations prevent this mechanism, the selection effect may not occur or it may be negative. In this way, Archaya and Keller examine the impact of rigidity in the product market institutions on the selection effect by using data on the regulation of entry from the World Bank Investment Climate Survey, and find that high entry barriers slow down the process of market share reallocation between firms that is induced by import liberalization.

Melitz (2003) suggests the labor market competition as the alternative mechanism to cause the selection effect. Therefore, to identify the role of rigidity in labor market institutions in the selection effect, my work builds on Melitz's (2003) argument on selection effect: after trade liberalization, the increase of average real wage induced by exports pushes up aggregate productivity through removing the least productive firms from the market. This increased average real wage reflects the increased labor demand that stems from incumbent exporters' capacity expansion and the new exporters' entry. However, while Melitz's model assumes a flexible labor market, the labor demand in reality has been troubled by rigidity in labor market institution, for example, Employment Protection Legislation (EPL). The continental European countries experienced with "Eurosclerosis", high unemployment due to slow job creation in 1970-80's relative to U.S. In the analysis of this phenomenon, EPL has been pointed out as one of the main determinants because it affects the labor demand negatively.

The negative impact of EPL on labor demand results from the increased firm's firing costs by EPL. Since a potential firm's decision to enter and an incumbent's decision to expand its capacity are mainly dependent not only on the increase of expected profits but also on the probability of failure, one of the critical determinants of these decisions should be the firing costs. In the same vein, Hopenhayn and Rogerson (1993) conclude that EPL perturbs the reallocation of resources from declining firms to more dynamic ones with above average productivity growth. Through using variation in the adoption of EPL across U.S. states, Autor, Kerr and Kugler (2007) find that the introduction of wrongful-discharge protections causes low employment flow and less firm entry. Furthermore, the studies connected to business cycle suggest more interesting evidence. According to Bentolila and Bertola (1990), Bertola (1990), Garibaldi (1998) and Messina and Vallanti (2007), stricter EPL decreases employment volatility (job creation and job destruction) over the business cycle because EPL affects both the incentives to hire and to dismiss workers. Consequently, the stringent EPL reduces job creation and slows the flow of labor resources into emerging high productivity firms.

Melitz (2003) and Davidson, Matusz, and Shevchenko (2008) consider job creation at the incumbent and new exporting firms as a catalyst for the selection effect of trade. However, EPL hinders the operation of this catalyst. Seker (2010) show that EPL discourages firms from exporting by using a rich set of firm level data from 26 countries in the Eastern Europe and Central Asia region.[44] This implies that the stringent EPL makes the incumbent and new exporting firms difficult to expand their capacity and enter the foreign market, which is likely to reduce the potential exports. Therefore, the export labor demand will not increase as much as in a more flexible labor market, which will not allow the real wage to rise sufficiently. As a result, firms with marginal productivity in a rigid labor market are more likely to survive than in a flexible labor market because the smaller increase in average real wage is affordable to firms with marginal productivity. This reduces the selection effect.[45]

Furthermore, the labor market rigidity can cause the negative selection effect of trade. Trade liberalization in developed countries forces us to consider the negative impact of increased imports on the average real wage in the same sectors influenced by increased exports because the intra-industry trade dominates. Kang (2010) finds the crucial role of labor market conditions in determining the impact of trade on average real wage by using U.S. dataset; that is, with low job destruction and job creation, the negative impact of imports on the average real wage exceeds the positive impact of exports, and therefore the effect of trade on the average real wage is likely to be negative. As mentioned above, EPL reduces job creation as well as job destruction. Therefore, the stricter the EPL is, the more likely that trade

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[44] Seker (2010) connects EPL to the investment climate for firms.

[45] This logic stems from Melitz's (2003) argument. Davidson, Matusz, and Shevchenko (2008) can also explain the relationship between the selection effect and EPL; that is, if there are a few job creation at the incumbent and new exporting firms, the workers with high ability in non-exporting firms do not have the chance to transfer toward the exporting firms much. Therefore, the inactive transfer of workers with high ability in non-exporting firms cannot accelerate the selection effect of trade.

causes the average real wage to decrease. The decreased average real wage will cause the negative selection effect of trade because it enables the least productive firms to start business and survive in this market. Accordingly, the direction as well as size of selection effect induced by trade liberalization is likely to be determined by labor market institutions such as EPL that affect firms' labor demand.

For the empirical approach, OECD countries provide a good laboratory because OECD countries trade with each other vibrantly and the characteristics of their labor markets are divergent. Due to this reason, this paper uses the Coe, Helpman, and Hoffmaister (2009) dataset and Nickell (2006) dataset. The former provides information on R&D capital stocks, Total Factor Productivity (TFP), openness to trade, and other variables in 24 OECD countries during 1971-2004, while the latter has information about two indexes of EPL in 19 OECD countries from 1960 to 2004. However, two indexes of EPL in Nickell (2006) do not vary much across time within country. So I construct a new EPL index as the average of the two indexes and the product of them. Since the new EPL indexes reflect information on each EPL index in Nickell (2006), they can have more variation across time.

In the dataset used for this research, there are more time-series observations than cross-section observations. Therefore this paper will conduct the panel unit root test and cointegration test.[46] For the panel unit test, I will introduce Levin, Lin and Chu (LLC, 2002), Im, Pesaran and Shin (IPS, 2003), Fisher in Maddala and Wu (1999) and Hadri (2000) tests. Pedroni (1999) test and Fisher test in Maddala

[46] As roughly suggested in Wooldridge (2002), when time-series observations is equal or greater than cross-section observation, we need the assumption about the nature of the time dependence and time series analysis.

and Wu (1999) are employed in order to check the panel cointegration in this paper. Under the cointegration relationship, Ordinary Least Square (OLS) is (super) consistent but it has a second order asymptotic bias in a small sample (Kao and Chiang, 1999). Thus this paper will use Dynamic OLS (DOLS) suggested by Kao and Chiang and Pedroni in order to fix OLS's problem.

This paper finds that the interaction term between openness to trade and EPL is negatively associated with TFP. In other words, as EPL becomes more stringent, the negative selection effect of trade would reduce TFP. In addition, according to the marginal effect of openness to trade, a country with extremely strict EPL but low foreign R&D capital stocks can have the experience with decreasing TFP after trade liberalization because the negative selection effect offsets the international R&D spillovers.

Te rest of the paper is organized as follows. I describe the estimation strategy and the data in Section II. The empirical results are presented in Section III. Section IV concludes.

III.2 Estimation Strategy

III.2.1 Model Specification

Following common practice in panel cointegration studies, this paper examines the impact of EPL on the selection effect as economy becomes more open to trade. The early studies regarding the impact of trade on aggregate productivity suggest two main channels, i.e. international R&D spillover and selection effect.

Coe, Helpman, and Hoffmaister (2009) investigated which institutions promote international R&D spillover. Particularly, they found that the labor market institution does not affect the international R&D spillover effect. However, as argued in the previous section, EPL is likely to be involved in the selection effect of trade because of raising firing costs. Therefore, in order to capture the two main channels, I extend the empirical equation in Coe, Helpman, and Hoffmaister (2009) by adding an interaction term between openness to trade and EPL ($m_{i,t} \times EPL_{i,t}$). As a result, one can expect in equation (1) that the impact of trade openness on TFP can be divided into international R&D spillover effect ($m_{i,t} \times \ln S_{i,t}^{f}$) and the selection effect ($m_{i,t} \times LMR_{i,t}$); that is, I can hypothesize that β_3 and β_6 are likely to have the positive and negative sign, respectively.

$$\ln TFP_{i,t} = \beta_1 + \beta_2 \ln S_{i,t}^{d} + \beta_3[m_{i,t} \times \ln S_{i,t}^{f}] + \beta_4 m_{i,t} + \beta_5 \ln S_{i,t}^{f} + \beta_6[m_{i,t} \times EPL_{i,t}] + \beta_7 EPL_{i,t} + \varepsilon_{i,t},$$

$$i = 1,\ldots,19,\ t = 1971,\ldots,2004 \quad \text{(Eq. (1))}$$

where i is a country index; t is a time index; $\ln TFP_{i,t}$ is the logarithm of total factor productivity (TFP); $\ln S_{i,t}^{d}$ is the logarithm of the real domestic R&D capital stocks; $\ln S_{i,t}^{f}$ is the logarithm of the real foreign R&D capital stocks; $m_{i,t}$ is openness to trade; $EPL_{i,t}$ is Employment Protection Legislation; $\varepsilon_{i,t}$ is a well-defined error.

In addition, this specification enables us to compare the relative magnitude of international R&D spillover effect and selection effect. It is important because of Archaya and Keller's (2007) argument that the negative selection effect can offset the international R&D spillover effects in the long run. Furthermore, equation (1) will tell us specific conditions under which trade can hurt the aggregate productivity. For this, I will report the marginal effects of openness to trade ($m_{i,t}$).

III.2.2 Data Description

This paper utilizes two datasets. The first dataset is the Coe, Helpman, and Hoffmaister (2009) dataset that provides information on TFP, openness to trade, domestic R&D capital stocks, foreign R&D capital stocks, etc in 24 OECD countries from 1971 to 2004. According to Coe, Helpman, and Hoffmaister, TFP is defined as the log of output minus a weighted average of labor and capital inputs using factor shares as weights. In the case of foreign R&D capital stocks, to address some critiques, they use three alternative weighting schemes: a bilateral-import weighted average of trading partners' domestic R&D capital stocks, the weighted average proposed by Lichtenberg and van Pottelsberghe (1998) and a simple average of trading partners' domestic R&D capital stocks. As shown in Lichtenberg and van Pottelsberghe (1998), their weighting scheme has less aggregation bias than Coe and Helpman's (1995) weighting scheme. So I will use this weighting scheme.

The other dataset is from Nickell (2006). This dataset contains several indexes related to labor market institutions in 19 OECD countries from 1960 to 2004. Among them, I choose two indexes of EPL because EPL can be used a proxy for firing costs. The first EPL index ($EPL\_N_{i,t}$) is the extended version of Nickell and Nunziate (2001) using the OECD labour market statistics data base. This EPL index's range is {0, 2} and increasing with the strictness of employment protection. The second EPL index ($EPL\_A_{i,t}$) is taken from Allard (2005) and ranging over {0, 5}. She offers EPL country EPL scores for 1950-2003, by reviewing changes of EPL documented by ILO's International Encyclopedia for Labor Law and Industrial Relations. Yet, although the data points of these EPL indexes are annualized, they do not vary sufficiently across time within country. Therefore, to reflect information on both the two EPL indexes, I construct a new index as the average of the two index and the product of the two indexes; that is, $EPL1_{i,t} = (1/2) \times \{EPL\_N_{i,t} + (2/5) \times EPL\_A_{i,t}\}$ and $EPL2_{i,t} = EPL\_N_{i,t} \times EPL\_A_{i,t}$.

Since the empirical analysis should use the overlapping part of the two above datasets, the sample in this paper includes 19 OECD countries from 1971 to 2004.[47] <Table 10> shows two kinds of summary statistics. According to Panel (a) in <Table 10>, Anglo-Saxon countries (ASC) have a higher growth of TFP on average than continental European countries (CEC).[48] In the case of openness to trade, the lower values in ASC are attributed to including bigger countries such as Canada and the U.S. because those indexes are calculated by dividing the real GDP. As expected, continental European countries have stricter EPL, while Anglo-Saxon countries have a more flexible labor market in terms of EPL. Panel (b) reports the minimum, average, and maximum values of variables in order to calculate the marginal effect of openness to trade.

[47] Some countries are excluded in this paper; Greece, Iceland, Israel, Portugal, and South Korea.

[48] Continental European countries (CEC) are Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, and Switzerland. Anglo-Saxon countries (ACS) are Australia, Canada, Ireland, New Zealand, U.K., and U.S.

III.3. Econometric Issues

III.3.1. Testing for integration

To identify a possible long run relationship, we have to start with verifying that all variables are integrated of order one in levels. Therefore, this paper employs the several panel unit root tests because no dominant performance of one test over the others for all cases considered: Levin, Lin and Chu (2002), Im, Pearan and Shin (2003), Maddala and Wu (1999), and Hadri (2000).

Levin, Lin, and Chu (LLC, 2002) propose a procedure using pooled t-statistic of estimator to evaluate the null hypothesis that all cross-sections contain a unit root against the alternative that all cross-sections are stationary. The major limitation of LLC test stems from assuming a common autoregressive structure for all of the series. To address this limitation, Im, Pesaran, and Shin (IPS, 2003) propose t-bar statistic. By using the mean of ADF statistics computed for each cross-section unit in the panel, IPS has the testing procedure to allow for simultaneous stationary and non-stationary series; that is, the alternative hypothesis allows for some (but not all) of the individual series to have unit roots. By Lindeberg-Levy central limit theorem, the standardized t-bar statistic converges to a standard normal distribution as $N \rightarrow \infty$ under the null hypothesis. Im, Pesaran, and Shin (2003) show that if the underlying ADF regressions have a large enough lag order, the t-bar test is generally better than the LLC test. Like IPS, the Fisher-type test that proposed by Maddala and Wu (1999) also relaxes the restrictive assumption of LLC test. The Fisher-type test is based on a combination of the p-values of the test-statistics for a unit root in each cross-sectional unit. The advantage of this test is that one can use different lag lengths in the individual ADF regressions and it can be applied to any unit root test derived.

Unlike LLC, IPS and the Fisher-type test, Hadri (2000) suggests the null hypothesis that there is no unit root in any of the series in the panel against the alternative of a unit root in the panel.[49] To evaluate it, Hadri derives a residual-based Lagrange multiplier test by extending Kwiatkowski, Phillips, and Shin (1992) method. Especially, testing for stationarity in a panel data has the advantage that as N grows the power of the test increases and the distributions of the test statistics get asymptotically normal. However, similar to LLC, Hadri test also are the common unit root test that assumes a common autoregressive structure for all of the series.

III.3.2. Testing for cointegration

Since valid economic inferences can be drawn under cointegrating relations, the result of the panel unit root tests forces us to check the cointegration relationship in panel data. The panel cointegration test is to examine whether the error term is stationary, which guarantees that the regression is not spurious. This paper uses two cointegration tests: Pedroni (1999) test and Fisher test in Maddala and Wu (1999). Pedroni (1999) proposes seven tests for the null hypothesis of cointegration that allows for heterogeneous intercepts and trend coefficients across cross-sections. The seven tests are categorized into the homogenous alternative

[49] DeJong and Whiteman's (1991) suggest that in deciding whether economic data are stationary or integrated, it is useful to perform test of the null hypothesis of stationarity as well as of a unit root.

hypotheses (the within-dimension test or panel statistics test in Pedroni) and the heterogeneous alternative ones (the between-dimension or group statistics test). The former is to assume the same autoregressive parameter across different countries in the unit root test for the residual, while the latter is to be based on averaging the individually estimated autoregressive for each country.

As an additional test for cointegration, this paper uses Fisher test in Maddala and Wu (1999). This is underlain by Johansen methodology that is a likelihood-based (LR) panel test of cointegrating rank in heterogeneous panel models based on the average of the individual rank trace statistics. The proposed LR-bar statistic is very similar to the IPS t-bar statistic.

III.3.3. Estimating the long run relationship

Under the cointegration relationship, an OLS estimator is (super) consistent, but it has a second order asymptotic bias in a small sample so that its standard errors are not valid (Kao and Chiang, 1999). To construct valid t-statistics, the Dynamic OLS (DOLS) estimator adds leads and lags of the first difference of the right-hand variables in equation (1). As a result, we can construct equation (2) from equation (1):

$$\begin{aligned}\ln TFP_{i,t} &= \beta_1 + \beta_2 \ln S_{i,t}^{d} + \beta_3[m_{i,t} \times \ln S_{i,t}^{f}] + \beta_4 m_{i,t} + \beta_5 \ln S_{i,t}^{f} + \beta_6[m_{i,t} \times EPL_{i,t}] + \beta_7 EPL_{i,t} \\ &+ \sum_{k=-K_i}^{K_i}\{\gamma_{2k}\Delta \ln S_{i,t-k}^{d} + \gamma_{3k}\Delta[m_{i,t-k} \times \ln S_{i,t-k}^{f}] + \gamma_{4k} m_{i,t-k} + \gamma_{5k}\Delta \ln S_{i,t-k}^{f} + \gamma_{6k}[m_{i,t-k} \times EPL_{i,t-k}] \\ &+ \gamma_{7k} EPL_{i,t-k}\} + \nu_{i,t},\end{aligned}$$

$$i = 1,...,19,\ t = 1971,...,2004 \quad \text{(Eq. (2))}$$

According to Kao and Chiang (1999), the within-dimension DOLS estimator outperforms the OLS and fully-modified estimators, especially in a finite sample. However, the DOLS estimator has the disadvantage in that the inclusion of lead differences and lagged differences in the regression reduces degrees of freedom in estimation and handicaps prediction. So this paper prefers the parsimonious model removing independent variables with t-ratio smaller than 1.5 in equation (2).

Pedroni (2001) also suggests another DOLS estimator, the group-mean dimension DOLS estimator. This method is to average the estimates that obtain from the conventional time series DOLS estimator applied to the ith country of the panel.[50] For example, the group-mean panel DOLS estimator for the coefficient β_2 in equation (1) is $\hat{\beta}_2 = N^{-1}\sum_{i=1}^{N}\hat{\beta}_2^i$, where $\hat{\beta}_2^i$ is the conventional time-series DOLS estimator applied to the ith country of the panel. And the associated t-statistics is computed as $t_{\hat{\beta}_2} = N^{-1/2}\sum_{i=1}^{N} t_{\hat{\beta}_2^i}$. According to Pedroni (2001), the group-mean dimension DOLS estimator has an advantage of a more flexible model due to allowing for heterogeneous cointegration vectors and appears to suffer from much lower small-sample size distortion than the within-dimension estimators. Therefore, to evaluate the robustness, this paper also reports the results of the group-mean DOLS estimator suggested by Pedroni.

[50] I use E-Views 7 in order to conduct the DOLS estimator applied to the *i*th country of the panel. E-Views 7 provides the automatic selection for the conventional time-series DOLS lags and leads and for long-run variance whitening regression.

III.4 Empirical Results

The results of unit root tests and cointegration tests are reported in <Table 11> and <Table 12>, respectively. According to <Table 11>, the results of panel unit root tests by the Hadri (2000), IPS, and Fisher (ADF) methods indicate that all variables are non-stationary, while the LLC tests show that the null hypotheses of unit root for some variables such as trade openness ($m_{i,t}$) are rejected at the 5% significant level. However, according to Maddala and Wu (1999) and Im, Pesaran, and Shin (2003), the Fisher (ADF) test and the IPS test are preferable to the LLC method. So we can consider all variables as being non-stationary.

<Table 12> shows the results of Pedroni and Fisher cointegration tests. According to the way to construct a new EPL index, equation (1) is divided into two types of estimations. Additionally, the parsimonious model also does cointegration test. First, the results of Fisher test in panel (b) reject the null hypothesis of no cointegration as well as that of at most 1 cointegrating equation at the 1% significant level. For equation (1), therefore, it implies that at least two cointegration vectors exist. According to Pedroni cointegration tests in panel (a), three out of seven test statistics indicate that the estimating models are cointegrated at 5% significance. In particular, the panel ADF-statistics and group ADF-statistics reject the null of no co-integration at 1% significance. In addition, Pedroni's (1995) Monte Carlo simulation shows that in the case of small samples, the power of the three group statistics (between-dimension statistics) with the

heterogeneous alternative hypotheses is higher than that of the four panel statistics (within-group statistics) with the homogenous ones. Consequently, we can regard the parsimonious estimation models as being panel cointegrated because two out of three group statistics in each estimation model do not accept the null at 1 % significance.

Since all variables in each specification are cointegrated according to <Table 12>, the within-dimension DOLS and group-mean dimension DOLS can be the preferred estimators. <Table 13> present the estimation results based on the within-dimension DOLS (column 1-2, 4-5) and the group-mean dimension DOLS (column 3, 6) estimators. In the same way as <Table 12>, equation (1) is divided into two types of estimation model, respectively. The estimation results in <Table 4> are similar to Coe, Helpman, and Hoffmaister (2009) except that this paper adds the interaction terms between openness to trade and EPL. In comparison with Coe, Helpman, and Hoffmaister (2009), the elasticity of domestic R&D capital stocks ($\ln S_{i,t}^{d}$) has the same significant sign at the 1% level although the elasticities' sizes are relatively big.[51]

The important point to note in <Table 13> is that the interaction terms between openness to trade and EPL in each column are negative and statistically significant at the 10% level. The higher the openness to trade is, the more the domestic TFP is likely to be affected by two main channels: the international R&D

[51] The coefficient of domestic R&D stock ($\ln S_{i,t}^{d}$) in Coe, Helpman and Hoffmaister (2009) is 0.095, while that is about 0.18 in this paper. This gap may come from excluding some countries and the human capital variable.

spillover effect and the selection effect. Since $m_{i,t} \times \ln S_{i,t}^{f}$ is included in equation (1) to capture the foreign R&D spillover effect, another interaction term ($m_{i,t} \times EPL_{i,t}$) is likely to reflect the selection effect of trade. Therefore, the negative coefficient of $m_{i,t} \times EPL_{i,t}$ implies that the stricter the EPL is, the more the TFP is likely to decrease due to the negative selection effect.

Since the marginal effect of openness to trade in equation (1) depends on the foreign R&D capital stocks and EPL, the results in <Table 14> show which conditions cause the negative selection effect to offset the foreign R&D spillover effects. This is related to Archaya and Keller (2007). Unlike Archarya and Keller (2007), who focus on the effect of product market competition, this paper pays more attention to the effect of labor market competition. Thus, this paper can suggest which labor market conditions enable the negative selection effect to crowd out the international R&D spillover effect. To do this, I calculate the derivatives of openness to trade at the minimum, average and maximum values of EPL, respectively, given the average of foreign R&D capital stocks. As shown in each column, the marginal effect of openness to trade decreases according to the increase in EPL. More interestingly, under the minimum of foreign R&D capital stocks and maximum of EPL, the marginal effect is significantly negative; that is, if a country with extremely high labor market rigidity but low foreign R&D capital stocks is open, the openness to trade could cause this country to experience decreasing TFP because the international R&D spillover effect is offset by the negative selection effect. To obtain more specific implications, I also present the TFP marginal effects of trade at the Continental European Countries' (CEC) average of EPL and foreign R&D capital stocks and at the U.S. average of them. The difference of the two marginal effects can shed crucial light on why the productivity gap between European countries and U.S. has been widen since 1970s.

The results in <Table 15> provide the suggestive evidence on the relationship between EPL and productivity. Looking at the empirical literature, the impact of EPL on productivity is ambiguous so far. Lagos (2006) argues that if stringent EPL raises reservation wages, average productivity can increase simply because firms become more selective and less productive matches are not realized. However, as the economy becomes more open to trade, the impact of EPL on reallocating workers across industries as well as between firms is more important. Wasmer (2006) suggests that since EPL induces the substitution of specific for general skills, it may have a negative effect on productivity in the presence of major shocks which cause workers to be reallocated across industries and make industry-specific skills useless. In a consequence, if trade openness works as shocks in the economy, the impact of EPL on aggregate productivity can be dependent on the level of trade openness. The marginal effect of EPL in <Table 15> supports this argument.

<Table 13> also reports the group-mean DOLS results. Those results enable us to evaluate the robustness of the within-dimension DOLS results. Although the magnitude of coefficients is somewhat different, the sign of coefficients is consistent

to that of coefficients in the within-dimension DOLS;[52] that is, Group-Mean columns in <Table 13> shows that the interaction terms between trade openness and EPL are negatively and significantly associated with the logarithm of TFP at the 1% level. Putting these results together, we can conclude that as the economy becomes more open to trade, EPL hurts the TFP by perturbing the selection effect.

III.5 Conclusion

This paper has investigated the impact of EPL on the selection effect as the economy becomes more open to trade by using panel cointegration techniques. I found that the interaction term between openness to trade and EPL is negatively associated with TFP. That is, higher labor market rigidity in an open economy reduces the TFP through the negative selection effect. In addition, according to the marginal effect of openness to trade, a country with extremely strict EPL but low foreign R&D capital stocks could have the experience with decreasing TFP after trade liberalization. Consequently, these results suggest that trade reforms and labor market reforms are likely to be complementary.

[52] The coefficients of interaction term between trade openness and EPL in the group-mean DOLS results are very bigger than these in the within-mean DOLS results. This is attributed to U.K. and U.S. Without these countries, the results are very similar to within-mean DOLS results.
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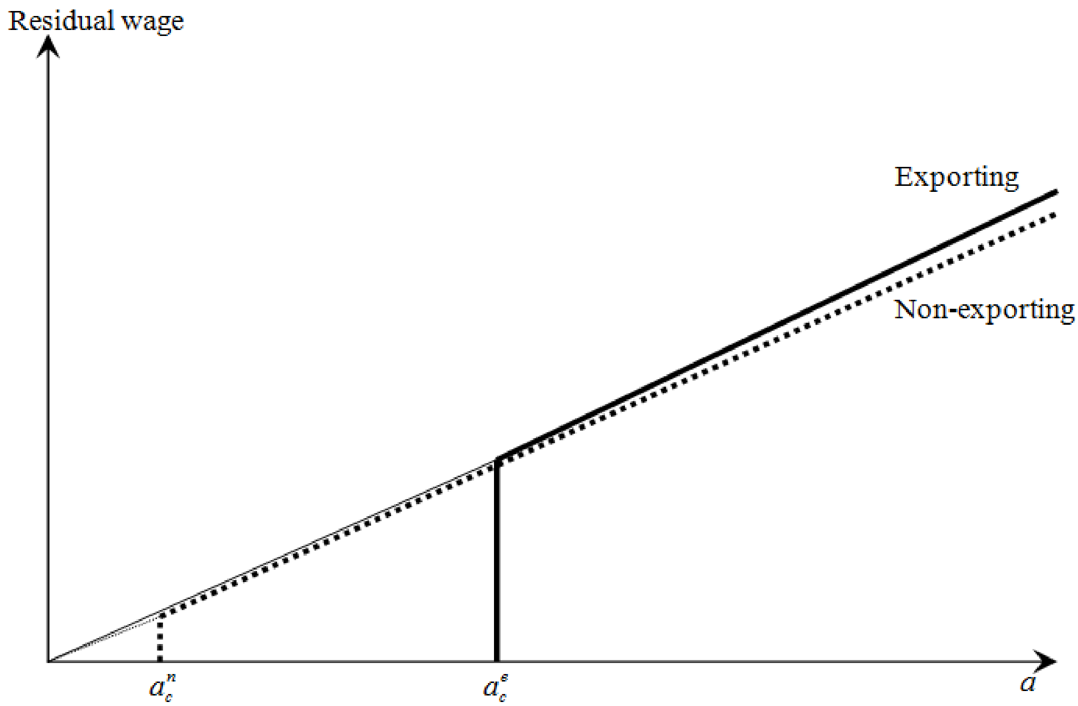
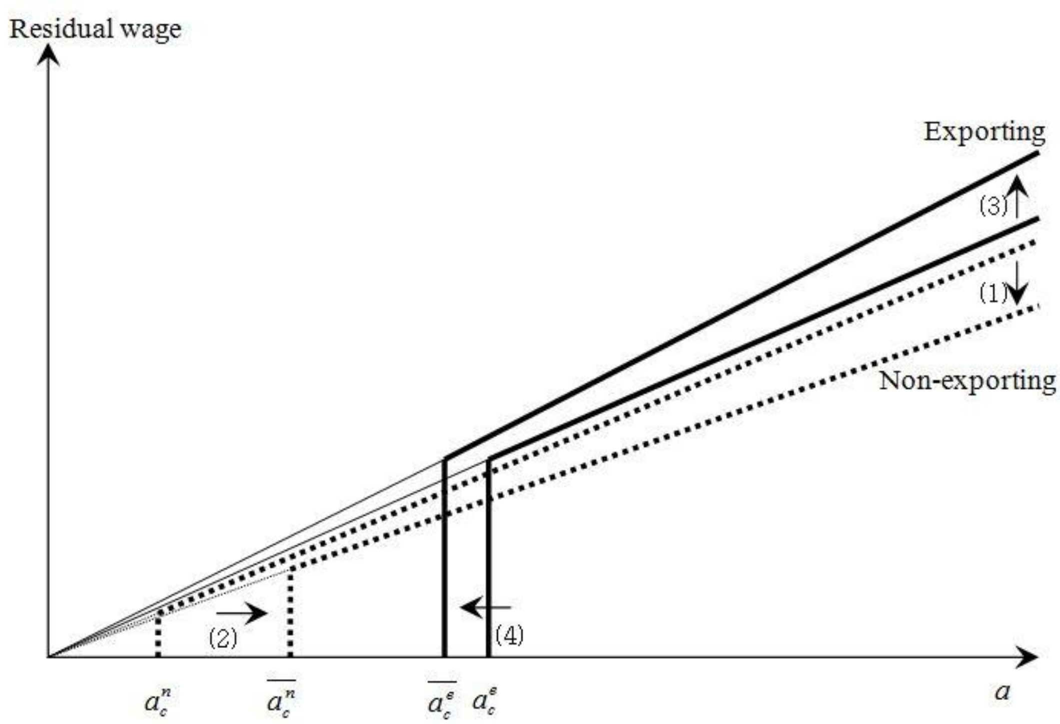
<Figure 1> The schedule of the residual wage to abilities in low degree of trade openness



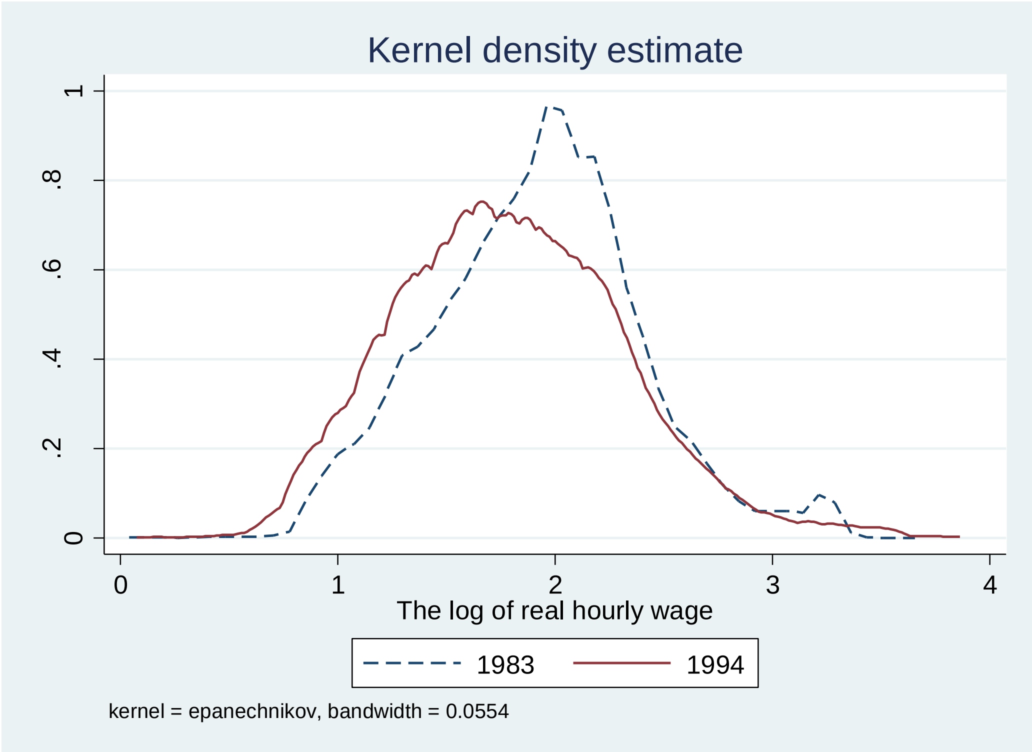
<Figure 2> The schedule of the residual wage to abilities in higher degree of trade openness



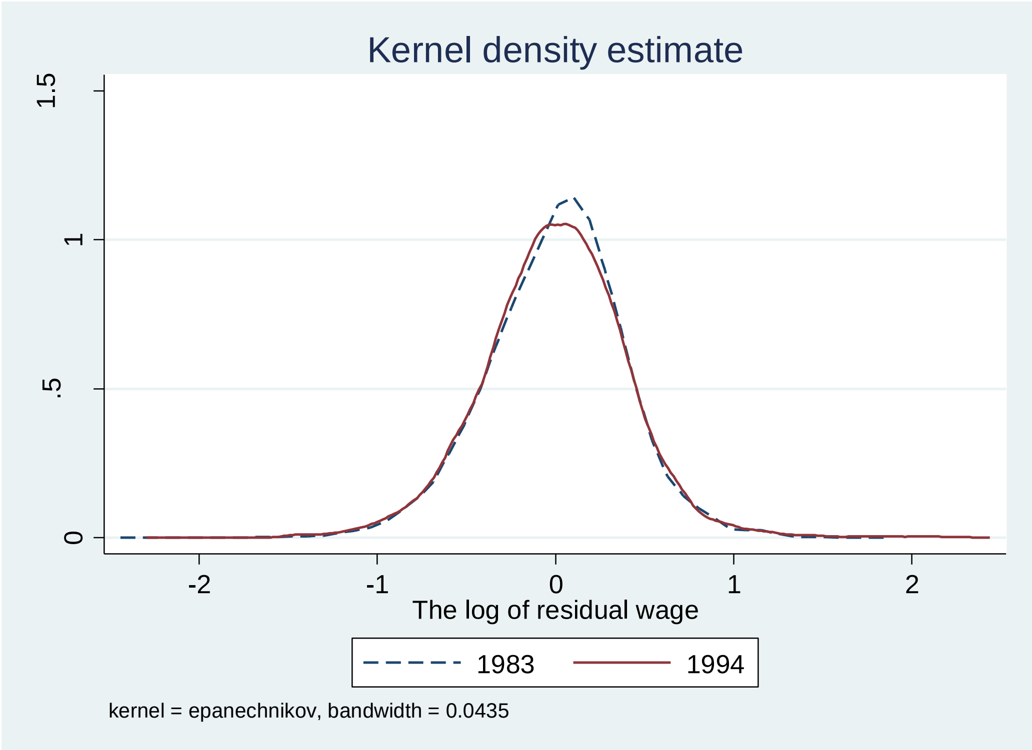
Notes: a_c^n is the cut-off of non-exporting firm. a_c^e is the cut-off of exporting firm.

<Figure 3> The distribution between 1983 and 1994 in the manufacturing sector

Panel (a): real hourly wage

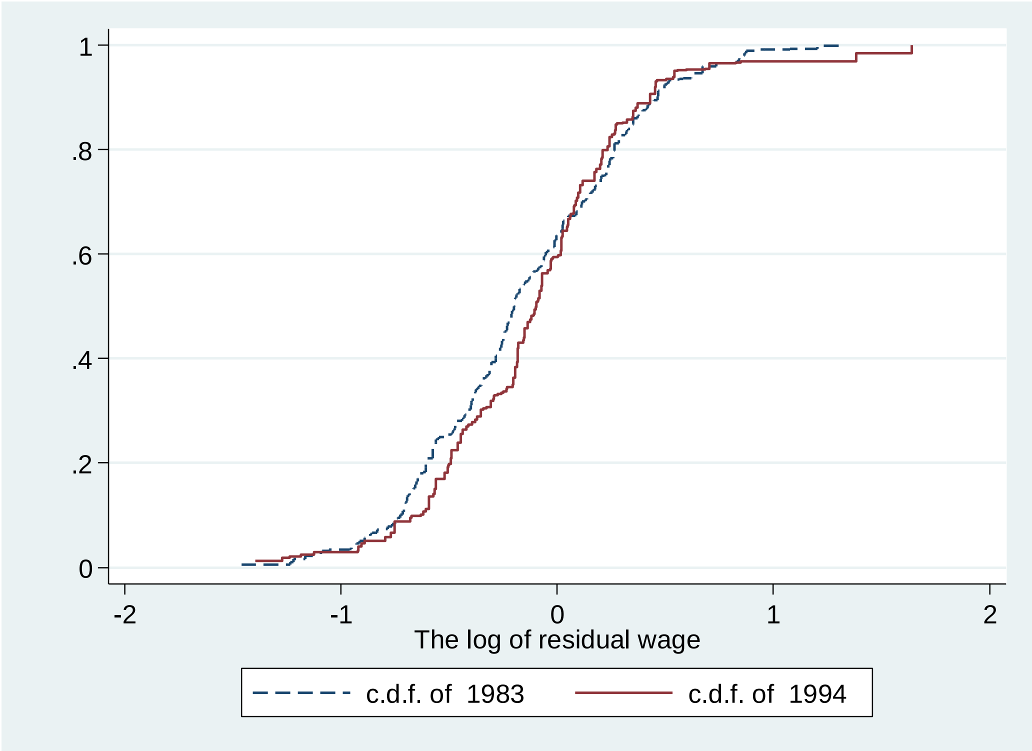


Panel (b): residual real hourly wage

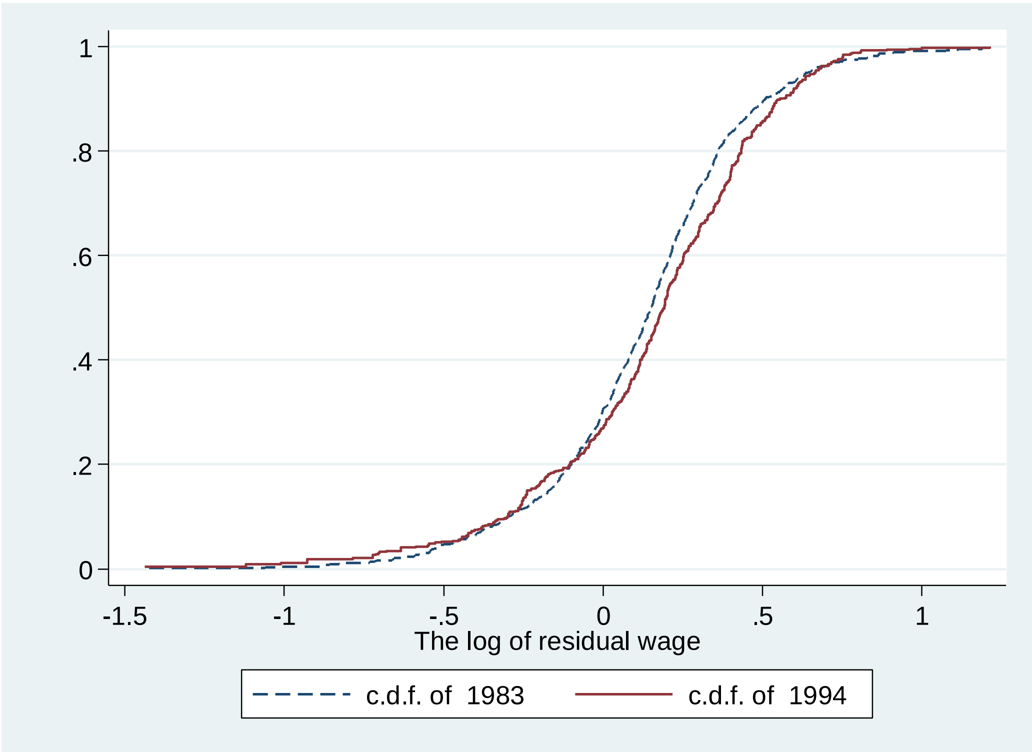


<Figure 4> Cumulative distribution functions of residual wages between 1983 and 1994 in the industries with a high change rate of import penetration and job destruction

Panel (a): Logging industry

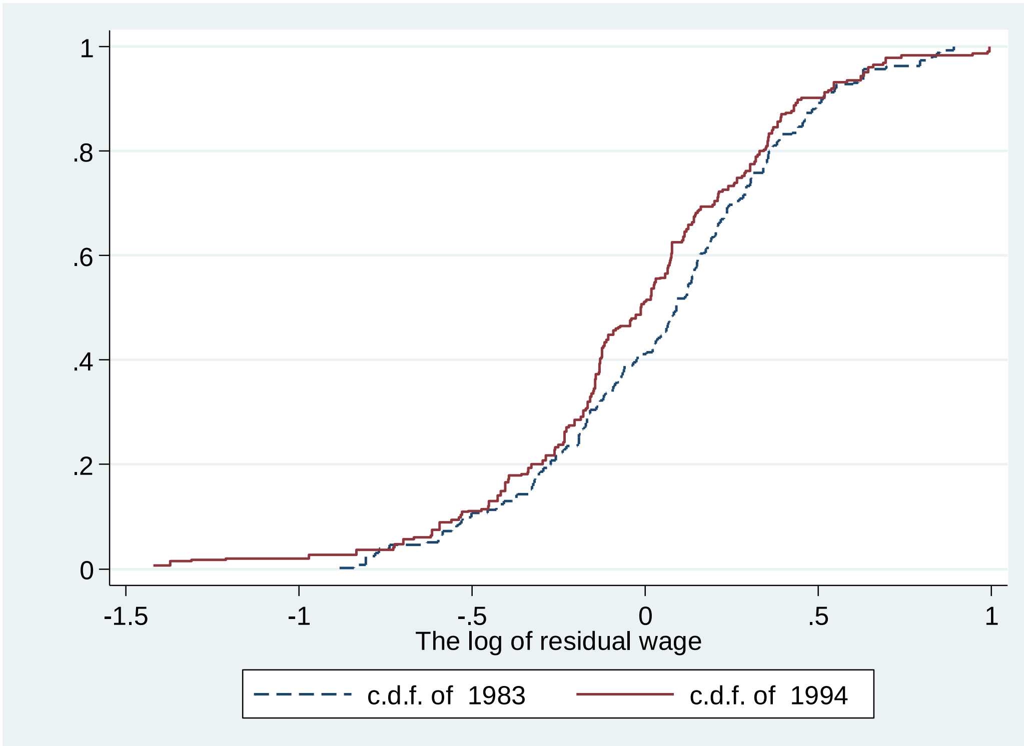


Panel (b): Office and Accounting machines industry

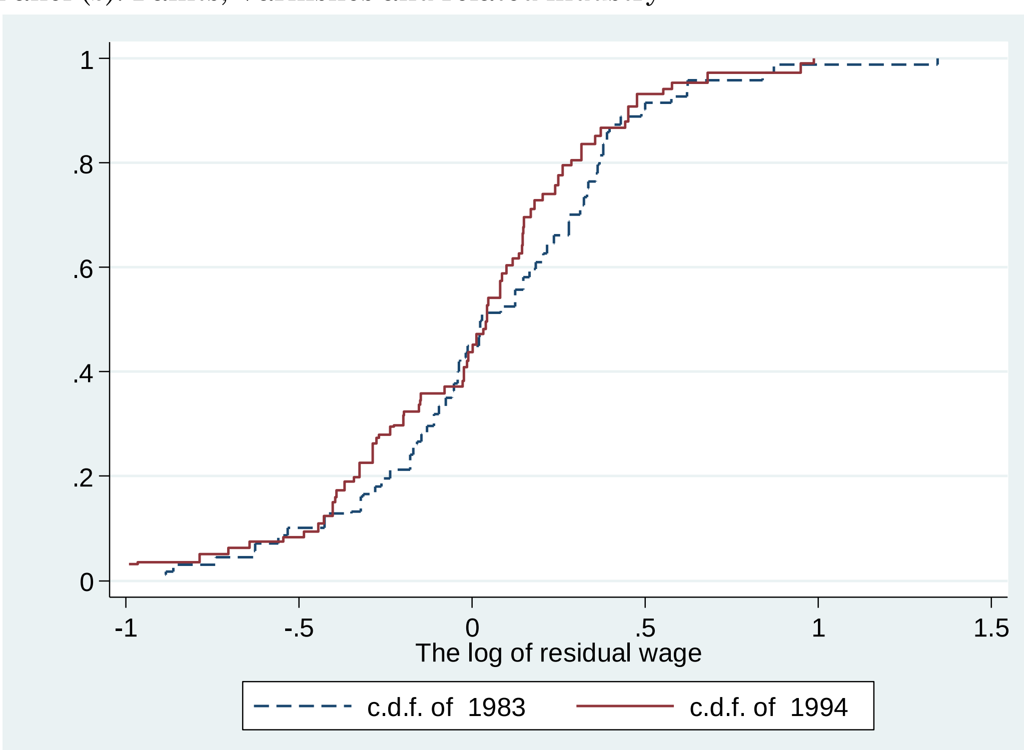


<Figure 5> Cumulative distribution functions of residual wages between 1983 and 1994 in the industries with a high change rate of import penetration but a low change rate of job destruction

Panel (a): Plastics, Synthetics and Resins industry



Panel (b): Paints, Varnishes and related industry



<Table 1> Regression results of a Mincerian equation

	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Exp	0.065	0.065	0.066	0.067	0.064	0.064	0.063	0.061	0.06	0.06	0.061	0.063
Exp2	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006
ed2	0.157	0.172	0.173	0.228	0.194	0.143	0.076	0.093	0.087	0.131	0.104	0.114
ed3	0.269	0.252	0.253	0.294	0.268	0.237	0.208	0.214	0.167	0.201	0.219	0.178
ed4	0.313	0.324	0.333	0.344	0.313	0.326	0.25	0.248	0.236	0.277	0.277	0.23
ed5	0.361	0.355	0.396	0.418	0.385	0.345	0.271	0.274	0.298	0.300	0.307	0.288
ed6	0.482	0.489	0.497	0.531	0.515	0.467	0.394	0.399	0.422	0.448	0.422	0.433
ed7	0.617	0.613	0.638	0.688	0.676	0.614	0.552	0.574	0.585	0.595	0.582	0.577
ed8	0.846	0.853	0.897	0.958	0.946	0.91	0.819	0.847	0.861	0.939	0.912	0.897
ed9	0.992	1.041	1.066	1.124	1.126	1.058	1.009	1.038	1.062	1.125	1.118	1.151
cons	-0.10	-0.13	-0.17	-0.25	-0.19	-0.15	-0.08	-0.08	-0.12	-0.16	-0.18	-0.23
R2	0.357	0.372	0.381	0.396	0.399	0.388	0.384	0.401	0.397	0.396	0.399	0.388
n	22528	23483	23600	23127	22518	21517	21855	22364	20966	20109	19438	18575
Stdev[b]	0.293	0.305	0.315	0.325	0.337	0.326	0.324	0.333	0.347	0.361	0.356	0.370
(ed8-ed6)[c]	0.364	0.364	0.400	0.427	0.431	0.443	0.425	0.448	0.439	0.491	0.490	0.464

Notes: [a]:Exp is the experience measured by a proxy variable, age. And the nine schooling dummies are for 0-4, 5-8, 10, 11, 12, 13-15, 16, and 17+. In order to avoid multicollinearity, the dummy for 0-4 is excluded. [b]:Stdev is the standard deviation of coefficients of ed2-ed9. [c]:(ed8-e6) represents the college premium.

<Table 2> Summary Statistics

	Obs.	Average	St.Dev.	Min	Max.
Average of log(residual wage)	888	-0.028	0.107	-0.347	0.273
10^{th} percentile of log(residual wage)	888	-0.500	0.132	-1.119	-0.042
Log(real shipment)	888	23.76	1.068	20.403	26.311
Union density	888	0.256	0.140	0	0.684
Import penetration	888	0.131	0.134	0.000032	0.800
Export propensity	888	0.084	0.086	0.000001	0.575
Tariff	876	0.047	0.036	0	0.228
Job creation	888	8.083	3.270	1.303	26.119
Job destruction	888	10.527	4.875	1.738	47.841

<Table 3a> Regression results: Dependent variable = Average residual wage

	OLS	Within	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
$Rwage_{s,t-1}$	0.846***	0.231***	0.755***	0.737***	0.785***	0.772***
	(0.019)	(0.071)	(0.079)	(0.086)	(0.084)	(0.087)
$\ln ship_{s,t}$	0.0024	0.0069	0.0031	0.0048	0.00021	-0.0038
	(0.0021)	(0.025)	(0.0036)	(0.0079)	(0.0075)	(0.0068)
$uni_{s,t}$	0.023*	0.091**	0.125	0.00034		
	(0.013)	(0.044)	(0.088)	(0.108)		
$neg_{s,t}$					0.0020	
					(0.0021)	
$pos_{s,t}$						0.0052
						(0.0039)
$\ln import_{s,t}$	-0.0035*	-0.0051	-0.011*	0.0091	-0.039***	-0.015*
	(0.0018)	(0.0078)	(0.0062)	(0.0099)	(0.014)	(0.0078)
$\times uni_{s,t}$				-0.053*		
				(0.028)		
$\times neg_{s,t}$					0.0019**	
					(0.00089)	
$\ln \exp ort_{s,t}$	0.0043**	0.0101*	0.016**	0.0034	0.021**	0.0027
	(0.0019)	(0.0053)	(0.0060)	(0.015)	(0.0083)	(0.0065)
$\times uni_{s,t}$				0.012		
				(0.040)		
$\times pos_{s,t}$						0.0015*
						(0.00086)
R2	0.811	0.693	.	.	.	.
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	814	814	814	814	814	814
AR(1)/AR(2)	/	/	0.00/0.599	0.00/0.569	0.00/0.466	0.00/0.471
Sargan			0.712	0.850	0.786	0.691

Notes: [a]: Robust standard errors are reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively. [b]: The standard errors in Within are corrected using a bootstrapping procedure. [c]: This system-GMM uses lags up to t-4 as instruments to avoid overfitting biases.

<Table 3b> Marginal effects of import penetration and export propensity in column 4

	Import	Export
Min	0.0078(0.0093)	0.0037(0.014)
Median	-0.0032(0.0068)	0.0063(0.0074)
Max	-0.024(0.013)*	0.011(0.012)

Notes: Standard errors are calculated by delta method and reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.

<Table 3c> Marginal effects of import penetration in column 5 and export propensity in column 6

	Import	Export
Min	-0.036(0.013)***	0.0047 (0.0060)
Median	-0.022(0.0079)***	0.015 (0.0065)**
Max	0.030(0.022)	0.043 (0.020)**

Notes: Standard errors are calculated by delta method and reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.

<Table 4a> Regression results: Dependent variable = 10th-percentile residual wage

	OLS	Within	SYS-GMM	SYS-GMM	SYS-GMM
$Rw_{s,t-1}$	0.644***	0.017	0.300**	0.317**	0.511***
	(0.041)	(0.054)	(0.147)	(0.153)	(0.168)
$\ln rship_{s,t}$	0.0077*	-0.0078	0.012	0.020	0.0069
	(0.0045)	(0.076)	(0.015)	(0.022)	(0.019)
$uni_{s,t}$	0.124***	0.201***	0.368*	-0.055	
	(0.030)	(0.059)	(0.214)	(0.285)	
$neg_{s,t}$					0.00003
					(0.0037)
$\ln import_{s,t}$	-0.0056	0.00020	-0.0047	0.0091	-0.059***
	(0.0040)	(0.0095)	(0.013)	(0.021)	(0.015)
$\times uni_{s,t}$				-0.092*	
				(0.055)	
$\times neg_{s,t}$					0.0033***
					(0.0013)
$\ln export_{s,t}$	0.0098**	0.011	0.029**	0.030*	0.057***
	(0.0040)	(0.0071)	(0.015)	(0.017)	(0.016)
R2/ Time Dummy	0.564/Yes	0.140/Yes	./Yes	./Yes	./Yes
Obs.	814	814	814	814	814
AR(1)/AR(2)	/	/	0.01/0.209	0.005/0.219	0.00/0.132
Sargan			0.384	0.398	0.762

Notes: [a]: Robust standard errors are reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively. [b]: The standard errors in Within are corrected using a bootstrapping procedure. [c]: This system-GMM uses lags up to t-4 as instruments to avoid overfitting biases.

<Table 4b> Marginal effects of import penetration in column 4 and 5

	Column 4 (union)	Column 5 (job destruction)
Min	0.0067 (0.020)	-0.053 (0.014)***
Median	-0.012 (0.018)	-0.028 (0.012)**
Max	-0.051 (0.030)*	0.065 (0.039)*

Notes: Standard errors are calculated by delta method and reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.

<Table 5> Regression results: Dependent variable = Average predicted wage

	OLS	Within	SYS-GMM
$Rw_{s,t-1}$	0.945(0.017) ***	0.292(0.051)***	0.893(0.050)***
$\ln rship_{s,t}$	0.0031(0.002)	0.024(0.038)	0.0041(0.0024)*
$uni_{s,t}$	-0.0017(0.0090)	-0.0047(0.027)	0.052(0.087)
$\ln imp_{s,t}$	-0.00094(0.0014)	-0.0064(0.0062)	-0.004(0.007)
$\ln \exp_{s,t}$	0.0013(0.0014)	0.00087(0.0049)	0.0090(0.0061)
R2 / Time Dummy	0.894 / Yes	0.622 / Yes	. / Yes
Obs.	814	814	814
AR(1) / AR(2)			0.00 / 0.516
Sargan			0.399

Notes: [a]: Robust standard errors are reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively. [b]: The standard errors in Within are corrected using a bootstrapping procedure. [c]: This system-GMM uses lags up to t-4 as instruments to avoid overfitting biases.

<Table 6a> Regression results of Tariff: Dependent variable = Average residual wage and 10th-percentile residual wage

Dependent variable	Average	Average	10^{th}	10^{th}
	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
$Rwage_{s,t-1}$	0.829***	0.858***	0.463***	0.473***
	(0.060)	(0.074)	(0.132)	(0.106)
$\ln rship_{s,t}$	0.0043**	0.0041	0.0024	0.013*
	(0.0021)	(0.0026)	(0.020)	(0.0071)
$uni_{s,t}$	0.057		0.169	
	(0.056)		(0.167)	
$neg_{s,t}$		0.000023		0.0080*
		(0.0016)		(0.0045)
$pos_{s,t}$		0.0068*		
		(0.0040)		
$\ln tariff_{s,t}$	-0.018	0.424	-0.689**	0.917
	(0.199)	(0.527)	(0.315)	(0.849)
$\times neg_{s,t}$		-0.012		-0.142**
		(0.021)		(0.068)
$\times pos_{s,t}$		-0.060		
		(0.047)		
R2 / Time Dummy	./Yes	./Yes	./Yes	./Yes
Obs.	803	803	803	803
AR(1)/AR(2)	0.00/0.778	0.00/0.498	0.00/0.160	0.00/0.217
Sargan	0.790	0.838	0.500	0.504

Notes: [a]: Robust standard errors are reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively. [b]: The standard errors in Within are corrected using a bootstrapping procedure. [c]: This system-GMM uses lags up to t-7 as instruments to avoid overfitting biases.

<Table 6b> Marginal effects of tariff in column 3 and 4

	Column 2 (job turnover)	Column 4 (job turnover)
Min	0.268(0.416)	0.549(0.689)
Median	-0.154(0.178)	-0.414(0.354)
75^{th}	-0.317(0.178)*	-0.806(0.322)**
Max or 99^{th}	-0.9302(0.558)*	-2.476(0.889)***

Notes: Standard errors are calculated by delta method and reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.

<Table 7> Regression results: Dependent variable = $\ln TFP_{s,t}$

	Model 1	Model 2	Model 3	Model 4
$\ln TFP_{s,t-1}$	0.892***	0.846***	0.933***	0.891***
	(0.035)	(0.012)	(0.040)	(0.027)
$\ln rship_{s,t}$	0.0027***	0.002****	0.0021***	0.0025***
	(0.00052)	(0.0059)	(0.0005)	(0.0006)
$neg_{s,t}$		-0.0011***		0.0001
		(0.00028)		(0.0003)
$pos_{s,t}$		0.0010**		0.001***
		(0.00050)		(0.00038)
$import_{s,t}$	0.0066*	-0.0043		
	(0.0035)	(0.0075)		
$\times neg_{s,t}$		0.0011**		
		(0.00052)		
$\exp ort_{s,t}$	-0.00031	0.0029		
	(0.0011)	(0.0041)		
$\times pos_{s,t}$		-0.00021		
		(0.00036)		
$\ln tariff_{s,t}$			-0.00034	0.108**
			(0.025)	(0.0044)
$\times neg_{s,t}$				-0.0033
				(0.0023)
$\times pos_{s,t}$				-0.0060**
				(0.0028)
Time Dummy	Yes	Yes	Yes	Yes
Obs.	7819	7819	6636	6636
AR(1)/AR(2)	0.00/0.529	0.00/0.818	0.00/0.383	0.00/0.443
Over-identification test	0.167	0.333	0.114	0.522

Notes: [a]: Robust standard errors are reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.

<Table 8> Marginal effects of import penetration, $\frac{\partial \ln TFP_{s,t}}{\partial imp_{s,t}} = \beta_5 + \beta_6 neg_{s,t}$, and marginal effect of export propensity, $\frac{\partial \ln TFP_{s,t}}{\partial \exp_{s,t}} = \beta_5 + \beta_6 neg_{s,t}$, from column 2 in <Table 7>

	Import		Export
Minimum $neg_{s,t}$	-0.0043 (0.0075)	Minimum $pos_{s,t}$	0.0029 (0.0041)
Average $neg_{s,t}$	0.0076 (0.0045)*	Average $pos_{s,t}$	0.0012 (0.0015)
Maximum $neg_{s,t}$	0.118 (0.054)**	Maximum $pos_{s,t}$	-0.0085 (0.016)

Notes: Standard errors are calculated by delta method and reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.

<Table 9> Marginal Effect of tariffs: $\frac{\partial \ln TFP_{s,t}}{\partial ltariff_{s,t}} = \beta_5 + \beta_6 neg_{s,t} + \beta_7 pos_{s,t}$

	$\ln TFP_{s,t}$
Minimum $neg_{s,t}$ and $pos_{s,t}$	0.108 (0.044)**
Average $neg_{s,t}$ and $pos_{s,t}$	0.022 (0.012)*
Maximum $neg_{s,t}$ and $pos_{s,t}$	-0.605 (0.295)**

Notes: Standard errors are calculated by delta method and reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.

<Table 10> Summary statistics

Panel (a)

	F_{04}/F_{71}	Sf_{04}/Sf_{71}	M_{04}	M_{71}	Epl_{04}	Epl_{71}	$Epl2_{04}$	$Epl2_{71}$
Australia	1.45	3.27	0.21	0.13	0.44	0.15	0.48	0
Austria	1.74	7.45	0.46	0.27	0.82	0.35	1.58	0.30
Belgium	1.80	5.36	0.80	0.47	0.91	0.65	1.97	0.71
Canada	1.35	4.04	0.34	0.20	0.38	0.16	0.32	0.03
Denmark	1.69	3.56	0.40	0.31	0.56	0.57	0.75	0.74
Finland	2.16	4.61	0.32	0.25	0.80	0.59	1.54	0.77
France	1.66	5.77	0.25	0.15	1.1	0.52	3.00	0.64
Germany	1.55	4.69	0.33	0.19	0.81	0.76	1.64	1.33
Ireland	3.72	5.93	0.69	0.41	0.47	0.23	0.52	0.12
Italy	1.51	5.69	0.25	0.15	1.00	1.18	2.14	3.48
Japan	1.72	4.21	0.11	0.09	0.58	0.68	0.84	1.14
Netherlands	1.57	5.47	0.59	0.47	0.83	0.81	1.68	1.62
New Zealand	1.15	2.77	0.30	0.22	0.41	0.19	0.40	0.06
Norway	2.42	3.22	0.29	0.38	0.98	1.05	2.35	2.72
Spain	1.44	11.14	0.30	0.12	0.98	1.15	2.37	3.19
Sweden	1.54	2.98	0.38	0.23	0.91	0.48	1.97	0.50
Switzerland	1.10	4.42	0.39	0.30	0.49	0.27	0.56	0.17
U.K.	1.78	6.52	0.28	0.21	0.40	0.20	0.32	0.09
U.S.	1.32	9.23	0.15	0.06	0.16	0.06	0.04	0.01
ASC	1.80	5.30	0.329	0.205	0.373	0.162	0.845	0.051
CEC	1.68	5.36	0.397	0.275	0.845	0.695	1.795	1.346

Notes: ASC (Anglo-Saxon countries) are Australia, Canada, Ireland, New Zealand, U.K., and U.S. CEC (Continental European countries) are Austria, Belgium, Demark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, and Switzerland

Panel (b)

	Obs.	Average	St.Dev.	Min	Max.
$TFP_{i,t}$: Total Factor Productivity	646	0.842	0.146	0.293	1.111
$S^d_{i,t}$: Domestic R&D	646	152042	356125	617	2448353
$S^f_{i,t}$: Foreign R&D	646	14474	15475	701	112422
$m_{i,t}$: Openness to trade	646	0.308	0.150	0.055	0.849
$EPL1_{i,t}$: $\frac{1}{2}\{EPL\_N_{i,t} + \frac{2}{5}EPL\_A_{i,t}\}$	646	0.699	0.361	0.055	1.405
$EPL2_{i,t}$: $EPL\_N_{i,t} \times EPL\_A_{i,t}$	646	1.515	1.301	0	4.902

Notes: In $EPL\_N_{i,t}$ and $EPL\_A_{i,t}$ are taken from Nickell (2006) and Allard (2005), respectively.

<Table 11> Panel unit root tests

	Common unit root tests		Individual unit root tests	
	LLC	Hadri	Fisher (ADF)	IPS
$m_{i,t}$	-1.870**	11.960***	44.180	-0.994
	(0.031)	(0.00)	(0.227)	(0.160)
$EPL1_{i,t}$	-0.900	7.589***	45.742	-0.407
	(0.184)	(0.00)	(0.128)	(0.342)
$EPL2_{i,t}$	-2.023**	6.362***	43.145	-0.171
	(0.022)	(0.00)	(0.192)	(0.432)
$\ln TFP_{i,t}$	-0.846	14.840***	30.013	1.001
	(0.199)	(0.00)	(0.819)	(0.842)
$\ln S_{i,t}^{d}$	0.082	14.944***	19.195	4.112
	(0.533)	(0.00)	(0.995)	(1.00)
$\ln S_{i,t}^{f}$	-4.155***	15.712***	18.400	1.475
	(0.00)	(0.00)	(0.997)	(0.930)
$m_{i,t} \times \ln S_{i,t}^{f}$	-0.258	13.761***	23.420	1.570
	(0.398)	(0.00)	(0.970)	(0.912)
$m_{i,t} \times EPL1_{i,t}$	5.815	13.276***	40.948	-1.197
	(1.00)	(0.00)	(0.342)	(0.116)
$m_{i,t} \times EPL2_{i,t}$	-2.179**	6.520***	45.432	-0.819
	(0.02)	(0.00)	(0.190)	(0.207)

Notes: (a) In Levin, Lin and Chu (2002) and Im, Pesaran and Shin (2002), the unit root is the null hypothesis to be tested whereas Hadir (2000) tests the null hypothesis of stationary. (b) Both tests are based on fixed effect model. *, **, *** indicate the parameters that are significant at 10%, 5%, 1% probability level respectively. In parenthesis, critical probabilities are given. (c) Tests are based on E-veiws7.0. All ADF tests include a constant, and the optimal number of lags is chosen according to modified Schwatz. The long run variance is estimated using the Bartlett kernel with automatic spectral window bandwidth selection as in Newey-West.

<Table 12> Panel cointegration tests

(a) Pedroni

		Eq. (1) with $EPL1_{i,t}$		Eq. (1) with $EPL2_{i,t}$	
			Parsimonious		Parsimonious
Panel	v	-1.282 (0.900)	-2.758 (0.997)	-1.410 (0.921)	-3.384 (1.00)
	rho	0.795 (0.787)	0.291 (0.615)	1.006 (0.843)	0.652 (0.743)
	PP	-2.226** (0.013)	-2.612*** (0.005)	-1.975** (0.024)	-2.609*** (0.005)
	ADF	-3.583*** (0.000)	-3.831*** (0.000)	-3.035*** (0.001)	-4.413*** (0.000)
Group	rho	2.790 (0.997)	0.693 (0.756)	2.908 (0.998)	2.286 (0.989)
	PP	-0.737 (0.230)	-3.475*** (0.000)	-0.622 (0.267)	-3.083*** (0.001)
	ADF	-3.115*** (0.001)	-6.917*** (0.000)	-2.763*** (0.003)	-6.921*** (0.000)

Notes: (a) Tests are based on the E-views 7.0. The optimal number of lags is chosen according to Schwarz. The long run variance is estimated using the Parzen spectral kernel with automatic spectral window bandwidth selection as in Newey-West (1994). (b) *, **, *** indicate that the test rejects the null of no cointegration at 10%, 5%, 1% probability level respectively. In parenthesis, critical probabilities are given.

(b) Fisher (combined Johansen)

Hypothesized # of CE(s)	Eq. (1) with $EPL1_{i,t}$		Eq. (1) with $EPL2_{i,t}$	
		Parsimonious		Parsimonious
None	709.1 ***	433.9***	693.1***	419.1***
At most 1	394.1 ***	234.8***	386.8***	228.9***

Notes: *, **, *** indicate that the test rejects the null of hypothesized number of cointegration at 10%, 5%, 1% probability level respectively. In parenthesis, critical probabilities are given.

<Table 13> lnTFP Estimation Results using DOLS

	Eq. (1) with $EPL1_{i,t}$			Eq. (1) with $EPL2_{i,t}$		
	Within	Within Pars.	Between Pars.	Within	Within Pars.	Between Pars.
$\ln S^d_{i,t}$	0.206***	0.196***	0.241***	0.208***	0.197***	0.293***
	(9.31)	(14.33)	(6.65)	(9.54)	(14.07)	(10.67)
$m_{i,t}$	-3.606***	-2.689***	-4.070***	-3.565***	-2.915***	-4.176***
	(-4.44)	(-3.51)	(-6.54)	(-4.30)	(-3.75)	(-7.49)
$\times \ln S^f_{i,t}$	0.421***	0.324***	0.520***	0.397***	0.327***	0.516***
	(5.51)	(5.48)	(4.05)	(5.16)	(5.07)	(6.89)
$\times EPL_{i,t}$	-0.801**	-0.756**	-2.356***	-0.243***	-0.211**	-2.494***
	(-2.05)	(-2.14)	(-2.95)	(-2.66)	(-2.50)	(-4.00)
$\ln S^f_{i,t}$	-0.043			-0.034		
	(-1.41)			(-1.17)		
$EPL_{i,t}$	0.227*	0.213**	0.879***	0.084***	0.076***	0.613***
	(1.93)	(2.06)	(2.67)	(3.18)	(3.06)	(3.03)
Leads/lags	1/2	1/2	Maxing 1	1/2	1/2	Maxing 1
CenteredR^2	0.900	0.896		0.903	0.900	
Obs.	646	646	646	646	646	646

Notes: (a) pars. is the parsimonious estimation model. (b) all regressions include unreported, country-specific constants. The conventional t-statistics are reported in parentheses. *, **, *** indicate the parameters that are significant at 10%, 5%, 1% probability level respectively.

<Table 14> Marginal Effect of trade openness: $\dfrac{\partial \ln TFP_{i,t}}{\partial m_{i,t}} = \beta_3 \ln S^f_{i,t} + \beta_7 EPL_{i,t} + \beta_5$

	Parsimonious model	
	with $EPL1_{i,t}$	with $EPL2_{i,t}$
Average $\ln S^d_{i,t}$, Min. $EPL_{i,t}$	0.221 (0.57)	0.076 (0.24)
Average $\ln S^d_{i,t}$, Average $EPL_{i,t}$	-0.278 (-1.19)	-0.255 (-1.14)
Average $\ln S^d_{i,t}$, Max. $EPL_{i,t}$	-0.800 (-2.98)***	-0.957 (-3.84)***
Max. $\ln S^d_{i,t}$, but Min. $EPL_{i,t}$	1.032 (2.81)***	0.891 (3.10)***
Min. $\ln S^d_{i,t}$, but Max. $EPL_{i,t}$	-1.596 (-4.47)***	-1.769 (-5.28)***
ASC's average: $\ln S^d_{i,t}$ and $EPL_{i,t}$	0.028 (0.09)	0.018 (0.06)
U.S.'s average: $\ln S^d_{i,t}$ and $EPL_{i,t}$	0.631 (1.78)*	0.513 (1.79)*
CEC's average: $\ln S^d_{i,t}$ and $EPL_{i,t}$	-0.452 (-2.06)**	-0.419 (-2.09)**

Notes: (a) ASC (Anglo-Saxon countries) are Australia, Canada, Ireland, New Zealand, U.K., and U.S.. CEC (Continental European countries) are Austria, Belgium, Demark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, and Switzerland. (b) The conventional t-statistics are reported in parentheses. *, **, *** indicate the parameters that are significant at 10%, 5%, 1% probability level respectively.

<Table 15> Marginal Effect of EPL: $\dfrac{\partial \ln TFP_{i,t}}{\partial EPL_{i,t}} = \beta_4 m_{i,t} + \beta_7$

	Parsimonious model	
	with $EPL1_{i,t}$	with $EPL2_{i,t}$
Minimum $m_{i,t}$	0.161 (1.98)**	0.061 (3.18)***
Average $m_{i,t}$	-0.023 (-0.53)	0.010 (1.20)
Maximum $m_{i,t}$	-0.429 (-2.06)**	-0.103 (-2.12)**

Notes: The conventional t-statistics are reported in parentheses. *, **, *** indicate the parameters that are significant at 10%, 5%, 1% probability level respectively.